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# Conglomerate Investment, Skewness, and the CEO Long Shot Bias

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June 30, 2015

## Abstract

Do behavioral biases of executives matter for corporate investment decisions? Using segment-level capital allocation in multi-segment firms (“conglomerates”) as a laboratory, we show that capital expenditure is increasing in the expected skewness of segment returns. Conglomerates invest more in high-skewness segments than matched standalone firms, and trade at a discount, which indicates overinvestment that is detrimental to shareholder wealth. Using geographical variation in gambling norms, we find that the skewness-investment relation is particularly pronounced when CEOs are likely to find long shots attractive. Our findings suggest that CEOs allocate capital with a long shot bias.

JEL Classification: G11, G31, G34

Keywords: Behavioral Corporate Finance, Skewness, Investment

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Making investment decisions that maximize shareholder value is the central task of corporate managers, and every MBA curriculum features state-of-the-art valuation tools prominently. Nevertheless, making investment decisions in the real world is difficult because even the best valuation tools rely to a considerable extent on assumptions that are subjective.<sup>1</sup> Consistent with substantial residual uncertainty around true project value, about half of the CEOs surveyed in Graham, Harvey, and Puri (2015) mention “gut feel” as an important or very important factor in their investment and capital allocation decisions. As there is by now overwhelming evidence suggesting that intuitive reasoning in financial matters frequently leads to biased and therefore suboptimal decisions, a natural – and potentially very important – question is if biases can distort optimal capital allocation in firms.

A central difficulty in this line of inquiry is that researchers do not usually observe the characteristics of individual projects to be chosen by corporate decision-makers. In this paper, we propose looking at segment-level capital allocation in multi-segment firms (“conglomerates”) as an identification strategy to circumvent this key problem.<sup>2</sup> Throughout our study, segments are defined as all operations by a firm in the same Fama-French 48 (FF48) industry. Since firms are required to disclose segment-level information, we can “look inside” conglomerates and study how biases affect capital allocation across segments.

A particular advantage of this approach is that prior research suggests a plausible link between capital budgeting and executive biases. CEOs are central to the capital allocation decision as they have “total and unconditional control rights” and can “unilaterally decide” what to do with a segment’s physical assets (Stein (2003)). Almost 40% of US CEOs say that they make capital allocation decisions with very little or no input from others according to a survey by Graham, Harvey, and Puri (2015). Hence, looking at capital allocation in conglomerates allows us to obtain a large sample of economically important investment decisions taken by individuals who self-report a tendency to rely on “gut feel.”

On this basis, our paper provides new evidence suggesting that managerial biases can lead to

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<sup>1</sup>As a simple example, suppose that the cash flow of a project is \$1 next year. The appropriate discount rate is 5%. Assuming a perpetual growth rate of 2% leads to a project value of \$33.3. Using an equally defensible growth rate of 3%, instead, one obtains a value estimate of \$50.0, which is 50.0% higher. Even with substantial resources spent on gathering relevant information, most valuation models will necessarily retain a significant subjective component, and two equally sophisticated individuals can obtain substantially different valuation results for most investment projects.

<sup>2</sup>The idea of using segment data to open up the black box of capital budgeting has a long tradition in the literature going back at least to Shin and Stulz (1998).

distorted capital budgets that do not maximize shareholder wealth. We focus on the implications of a powerful behavioral phenomenon which we label the “CEO long shot bias.” The CEO long shot bias is shorthand for a tendency of CEOs to systematically overvalue projects with high perceived upside potential (proxied for by expected skewness in our empirical tests). One prominent potential source of the phenomenon is prospect theory’s probability weighting feature, but, as we discuss in greater detail below, there may also be other deep drivers. We posit that the special authority of conglomerate CEOs in capital allocation decisions, and the fact that assumptions in valuation models are partly subjective, allow the CEO long shot bias to affect capital budgeting. CEOs subject to the bias will destroy shareholder wealth by investing too much in segments with high perceived upside potential.

To fix ideas, consider a simple example of a hypothetical conglomerate with two segments, A and B. The CEO oversees a fixed investment budget of  $I = 5$  for new projects that she can either allocate to segment A or to segment B. Segment A proposes the following project:

$$[(2, 0.4); (8, 0.6)]$$

This project generates a present value of cash flows, discounted at the appropriate risk-adjusted rate, before investment of 2 in the low state, which occurs with a probability of 0.4, and 8 in the high state with probability 0.6. Segment B proposes a project with a more skewed payoff distribution.

$$[(2, 0.9); (30, 0.1)]$$

This project yields 2 in the low state, which has a probability of 0.9. There is a 10% chance, however, that project B is a major success and the value before investment is then 30. Based on these numbers, because the expected NPV of project A is 0.6, and the expected NPV of project B is  $-0.2$ , a rational CEO should allocate the budget to project A. By contrast, if the long shot bias is strong enough, a CEO may nevertheless invest in project B and therefore destroy shareholder wealth.

In the first part of our paper, we show the above example is consistent with actual investment patterns in the Compustat universe of U.S. conglomerates from 1990 to 2009: capital expenditure is significantly higher for segments with projects that have higher expected skewness. The effects are

particularly pronounced for smaller segments, which, as we detail below, is predicted by the CEO long shot hypothesis. The positive relation between expected skewness and investment is robust to a battery of standard controls and additional checks, including firm and segment fixed effects.

When we match conglomerate segments to comparable standalone firms, we find that investment in conglomerates is significantly higher when skewness is high, even though we control for potentially greater debt capacity and other known factors. In fact, among standalones there is no skewness-investment relation once we control for industry-specific effects. This, together with a number of additional tests, indicates that high skewness is not simply proxying for good investment opportunities.

Looking at value implications, we find that conglomerate firms with skewed segments are valued by the market at significant discounts. These tests use the method of Berger and Ofek (1995), adjusted to control for endogeneity of the diversification decision with fixed effects, instrumental variables techniques, and selection models, as in Campa and Kedia (2002). As in our simple motivating example above, this suggests that conglomerates overinvest into segments with high expected skewness and that this investment behavior is detrimental to shareholder wealth.

These empirical patterns are potentially consistent with a number of channels other than the CEO long shot bias. First, the project with more skewed returns (project B) might be harder to value and therefore more prone to idiosyncratic valuation errors. Agency theory delivers a second possible explanation. Under this view, CEOs strategically exploit subjectivity in valuations to tilt capital budgets towards an allocation that maximizes private benefits (e.g., Scharfstein and Stein (2000), Rajan, Servaes, and Zingales (2000)). Our analysis shows that random valuation mistakes or agency problems cannot easily explain the skewness-investment relation we document.

We propose, and provide evidence for, a third channel: managers subject to the long shot bias choose project B *because* it offers a larger upside potential and a smaller winning probability than project A. For example, if the long shot bias is due to prospect theory's probability weighting feature, a CEO would choose project B because she evaluates the winning probability  $p = 0.1$  for project B *as if* it were a probability of 0.15. This leads to an estimated NPV of 1.2, which is higher than the NPV of project A. Under this scenario, a CEO would choose project B even if there was no disagreement about the true probability 0.1. Of course, in most relevant cases, it will be practically impossible to tell if there is a 10% or 15% chance that the project will be a

success, so there is every possibility for the CEO to ex post rationalize any decision close to her, potentially subconscious, preference. Another plausible driver of the long shot bias is anticipation utility: CEOs go for project B because it feels especially good to win big (e.g., Brunnermeier and Parker (2005)).

Valuation subjectivity greatly amplifies the potential for the long shot bias to affect capital allocation because any decision on which project to fund will have to rely at least partly on intuitive reasoning. Kahneman (2011) argues that a standard procedure of our cognitive apparatus is substituting a difficult question (e.g., “what is the probability that the project will be a success?”), with a simpler question (e.g., “can I easily think of instances where similar projects were a success?”). Because we construct our skewness measure from outcomes of similar projects in the recent past, high expected skewness will by definition be associated with instances of recent successes that will come to mind easily. Substitution and the availability heuristic would then lead to particularly optimistic forecasts for positively skewed projects. All three deeper drivers of the long shot bias – probability weighting, anticipation utility, and the availability heuristic – lead to the same outcome: the long shot project B is chosen and this destroys shareholder wealth. Because our aim in this paper is to show that the long shot bias has measurable and economically substantial effects on the efficiency of capital budgets, we leave identifying the ultimate source of the bias for future research.

We provide a direct test of the CEO long shot bias hypothesis by exploiting exogenous variation in the CEO’s propensity to gamble. Specifically, we use CPRATIO, a variable developed by Kumar, Page, and Spalt (2011), that captures gambling propensity of decision makers in a geographical area. CPRATIO is based on local religious beliefs and associated gambling-norms, so it is plausibly exogenous with respect to capital allocation decisions. When we split our sample according to the CPRATIO measure, we find that the skewness effects are concentrated where gambling propensity is high. We argue that this test is particularly informative because it raises the bar for any alternative explanation of our results: any candidate variable must not only be positively correlated with the propensity to invest in skewed project B. It must also be positively correlated with CPRATIO, that is, the fraction of Catholics in the county of the company headquarters. As an example, misaligned risk-taking incentives from inefficient contracting does not easily explain our specific set of results as it is not obvious why inefficient contracting should be more of a problem in Catholic regions.

Additional evidence supports the hypothesis that the skewness-investment relation is induced

by CEOs who are attracted to long shots. Using data on regional lottery ticket sales, we find that investment in skewed segments is particularly high when people around the headquarter buy more lottery tickets, that is, when the local gambling propensity increases. The skewness-investment relation is stronger for younger CEOs and for CEOs who are more powerful in their organization. In sum, we conclude that our evidence on the skewness-investment relation is consistent with a theory of distorted capital budgets due to the CEO long shot bias.

Our empirical evidence is in line with anecdotal evidence suggesting the CEO long shot bias can lead to serious inefficiencies in capital allocation. For example, the TV show CBS 60 Minutes aired a piece titled “Who killed Montana Power?” in 2003, which tells the story of a former Montana-based utility company with a small telecom segment. Montana Power radically redistributed resources from its utility to its telecom business in 1999, according to the feature: “to join the dot.com revolution by transforming itself into a high-tech telecommunications company called Touch America.” Losses for shareholders were enormous following the move (the company is now bankrupt). The CEO long shot bias would predict overinvestment in telecom when telecom looks attractive as a long shot relative to utilities. Indeed, our data show that, as of late 1999 the difference in skewness between telecom and utility industries was up by 250% relative to the year before. The CBS program provides additional evidence consistent with the view that the move was largely due to a CEO focusing too much on long shot upside potential by quoting a former Montana Supreme Court judge who said: “He [the CEO] was tired of what he thought was a stodgy utility stock... I think he wanted to be the Bill Gates of Montana. I think he wanted to get into a high flier situation where he could go to a \$100 a share instead of sit there at \$30.” While this example is rather extreme (which is why it was on TV), and while one needs to be cautious about drawing strong conclusions from individual cases, the story illustrates how the CEO long shot bias can matter for corporate investment decisions.

Our novel findings contribute to a branch of behavioral corporate finance which Baker and Wurgler (2011) label “irrational manager-rational markets” approach. Related papers include Malmendier and Tate (2005), who analyze investment-Q-sensitivity for overconfident managers, and Kruger, Landier, and Thesmar (2015), who study capital allocation when firms use the same discount rate across segments. We share with the latter paper the general notion that the conglomerate structure, to some degree, allows executives to make behaviorally driven suboptimal decisions for

shareholders. To the best of our knowledge, our paper is the first to document that skewness is related to inefficiencies in capital budgeting and the first to suggest that the CEO long shot bias can contribute to seriously distorted corporate investment decisions.

Section I presents the theoretical framework and the data. Section II documents the skewness-investment relation and its value implications. We present evidence for the CEO long shot bias explanation in Section III. Section IV discusses alternative explanations. Section V concludes.

## **I. Theoretical Framework and Data**

### **A. The CEO Long Shot Bias**

Our focus on the CEO long shot bias is motivated by a large body of prior work which documents that decision makers often find long shot bets attractive. For example, in early contributions, Friedman and Savage (1948) and Markowitz (1952) analyze the widespread demand for lottery tickets. In their work on prospect theory, Kahneman and Tversky (1979) and Tversky and Kahneman (1992) establish that the subjective valuation of a gamble increases in its skewness, and that, for small probabilities of large gains, certainty equivalents frequently exceed expected values. Kachelmeier and Shehata (1992) provide field evidence to show that this behavior is also present when stakes are large.

Prospect theory captures this preference for long shots by introducing a probability weighting function, a non-linear transformation of objective probabilities into subjective decision-weights, which has gained extensive support from experimental work (see, e.g., Fehr-Duda and Epper (2012) for a review). A growing literature in finance analyzes its asset pricing implications (e.g., Barberis and Huang (2008)). Outside finance, probability weighting has been used to explain buying of lottery tickets, casino gambling, and betting on horse-races (e.g., Barberis (2012), Snowberg and Wolfers (2010)). In a recent review article, Barberis (2013) writes that: “in risk-related fields of economics such as finance, insurance, and gambling, there is now more empirical support for probability weighting than for loss aversion, an arguably better-known component of prospect theory.”

While prominent in the literature, probability weighting is not the only way to capture a preference for positive skewness. Alternative theories include models of optimal beliefs, anticipation



utility, and salience (e.g., Brunnermeier and Parker (2005), Bordalo, Gennaioli, and Shleifer (2012), Jouini, Karehnke, and Napp (2014)). In our paper, we remain agnostic about which underlying mechanism induces a desire for positively skewed outcomes. We simply build on the fact that a preference for long shot bets is a widely documented phenomenon, supported by both data and theory. For short, we label the phenomenon that decision-makers like positively skewed bets with large upside potential the “long shot bias.”

A central novelty in our paper is to suggest that CEOs – just like most other decision-makers – are subject to the long shot bias. This shift in perspective is potentially important. First, CEOs make particularly hard decisions in which even the best available valuation tools leave substantial room for gut feeling, and therefore biases. Second, because the corporate hierarchy gives CEOs substantial decision-making power, biases in their decision-making are likely to translate into sub-optimal corporate actions. Finally, if the CEO long shot bias affects corporate investment, it influences the core of the economy directly.

We view the CEO long shot bias as a natural first step in thinking about the behavioral factors behind the term “gut feeling”, which, as we noted above, CEOs mention as an important input in their investment decisions. Whether and which other biases matter as well is a question we leave for future research.

## B. Conglomerate Investment and the CEO Long Shot Bias

We now offer a simple theoretical framework to think about the effect of the CEO long shot bias on capital allocation in conglomerates. Because we remain agnostic about the ultimate driver of the long-shot bias, we focus on the general mechanism in a reduced-form setting.<sup>3</sup>

Consider a conglomerate with two segments in different industries. The CEO’s task is to maximize shareholder value  $V$  by optimally allocating a total investment budget  $\bar{I}$  across the two segments:

$$\max_{I_1, I_2} V = f(I_1) + g(I_2), \quad (1)$$

where  $f(\cdot)$  and  $g(\cdot)$  are standard decreasing returns to scale technologies operated by segments 1 and 2, respectively, and where  $I_1 + I_2 = \bar{I}$ . There are no frictions, so the CEO would allocate

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<sup>3</sup>In the Internet Appendix, we present an alternative version of the model using the mean-variance-skewness portfolio choice framework (e.g., Mitton and Vorkink (2007), Harvey, Liechty, Liechty, and Müller (2010)).

the budget to segments such that allocating one additional dollar to segment 1 yields the same marginal benefit in terms of shareholder value as allocating an additional dollar to segment 2, that is  $f'(I_1^*) = g'(I_2^*)$ , assuming an interior solution.

While equating marginal values is simple in theory, it is hard in practice, because CEOs do not know true value generated. They make decisions based on an *estimate* of value. But even the best valuation tools (e.g., DCF) are imprecise and depend on assumptions that are often hard to pin down with much confidence. As result, personal judgment and gut feeling may systematically distort CEO's value estimates, and therefore investment decisions.

To see how the CEO long shot bias affects capital allocation, assume now that the first segment has high perceived upside potential, denoted by  $s > 0$  ("skewness"). For example, the segment may operate in the high-tech sector in 1999, which was considered "hot" at the time. Normalize the perceived upside potential of segment 2 to zero. A CEO subject to the long shot bias systematically overvalues segments with high perceived upside potential, that is, instead of maximizing true value  $V$  in equation (1), he maximizes the subjective estimate of value:

$$\max_{I_1, I_2} V^S = (1 + \gamma s) f(I_1) + g(I_2), \quad (2)$$

where  $(1 + \gamma s)$  captures overvaluation, and where  $\gamma > 0$  governs the degree of overvaluation for a given level of  $s$ . The first order condition then becomes  $(1 + \gamma s) f'(I_1^*) = g'(I_2^*)$ . This yields the following predictions that guide our empirical work below (proofs omitted):

PREDICTION 1: *All else equal, investment increases in a segment's perceived upside potential  $s$ .*

We label this effect "the skewness-investment relation."

PREDICTION 2: *The higher  $\gamma$ , the stronger the skewness-investment relation.*

A number of factors will influence  $\gamma$ , including segment size (as we discuss below), the strength of the long shot bias for a given CEO, and managerial discretion.

PREDICTION 3: *A CEO subject to the long shot bias destroys shareholder value by distorting the capital budget.*

**The Impact of Segment Size.** The Graham, Harvey, and Puri (2015) survey shows that gut feel decision-making is more prevalent in smaller businesses. Relatedly, we posit that the skewness-investment relation in conglomerates would be stronger for smaller segments, that is, we hypothesize  $\gamma$  is smaller for larger segments. As we now explain, this applies to both relative and absolute segment size. A particular advantage of our conglomerate setting is that we can use variation in segment size, both within and across conglomerates, as an additional source of identification in our empirical work. There are several, not mutually exclusive, reasons for why size should matter.

First, large segments, both absolute and relative, are often in a more mature stage of their life-cycle and work with established technologies that are easier to value. And the largest businesses in an industry often have the most skilled employees. Subjectivity in valuations, and reliance on gut feeling, may therefore be more relevant for smaller segments with newer technologies, less skilled employees, and less fine-tuned valuation models.

Second, attention effects suggest investment is more responsive to skewness in smaller segments.<sup>4</sup> Attention can matter on two levels. First, a CEO may devote more time and attention to the largest segments in the conglomerate. Hence, biases may be more likely to affect relatively small segments. Second, absolute segment size is related to attention paid by outsiders. For example, consider 3M's Electro and Communication Business, which is relatively small within 3M (11% of total sales in 2008), and Servotronics Inc.'s Electric Equipment segment, which is the largest segment of that firm (61% of total sales in 2008). In absolute size 3M's segment is more than 100 times larger (\$2.8bn vs. \$21m). It is therefore much more in the focus of investors, analysts, and the media. If those outsiders generate useful information for the CEO, this reduces the likelihood of a bias distorting optimal investment policies.

Third, according to Graham, Harvey, and Puri (2015), gut feeling and personal judgment may be more important for decisions in absolutely smaller businesses because small businesses have fewer highly visible peers to which to compare themselves.

The above reasons suggest that the CEO long shot bias should matter more for investment in small segments, both absolute and relative. In our empirical work, we therefore use a measure of small segments that combines relative and absolute size attributes. In the robustness tests, we also show that both, relative size and absolute size, work separately.

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<sup>4</sup>We thank an anonymous referee for this suggestion.

### C. Compustat Data

Our sample is based on the Compustat Segment files, covering the 20-year period from 1990 to 2009. We only include business segments and operating segments that are organized divisionally. We retrieve information on assets, sales, capital expenditures, operating profits, depreciation, and the 4-digit SIC code for each segment. We define a segment’s industry based on its primary SIC code (`ssic1`). If it is not available we use the primary SIC code for business segments (`ssicb1`). If both variables are missing we drop the observation. All duplicates of segment-year observations are deleted and we only keep the first observation from the original 10-K report. In the next step we merge the segment data with firm-level data from the Compustat Fundamentals Annual database. In order to ensure consistency between both databases we remove all observations where the sum of segment sales does not fall within 5% of total firm sales. We also drop all observations where sales or total assets are missing, zero, or negative. All firms which are in the Compustat Fundamentals Annual database but not in the segment data set are treated as single segment (“standalone”) firms. Finally we match the 4-digit SIC code of all segments and standalone firms with the corresponding Fama-French 48 (FF48) industry and aggregate within each firm all segments in the same FF48-industry into one segment. All firms active only in one FF48-industry are treated as standalone firms. Conglomerate firms are firms operating in more than one FF48-industry. We drop segments and firms with (i) assets less than \$1 million in 1993 dollars, (ii) anomalous accounting data (negative depreciation, capital expenditures less than zero, negative book equity, cash flow over assets less than -1), and (iii) missing or zero market capitalization.

### D. Skewness Measure

Our main explanatory variable is the expected skewness of segment returns,  $Skew$ . Since expected skewness on the segment level is not observable because segments do not have traded stock, we follow Zhang (2006) and Green and Hwang (2012) and use an industry-level approximation. Specifically, we construct for each segment  $i$  in fiscal year  $t$ :

$$Skew_{SEG,it} = \frac{(P_{99} - P_{50}) - (P_{50} - P_1)}{(P_{99} - P_1)}, \quad (3)$$

where  $P_j$  is the  $j$ -th percentile of the pooled return distribution of daily returns of all firms with share codes 10 and 11 in CRSP in the same FF48-industry as segment  $i$  over the 12 months prior to and including the last month of the conglomerate’s fiscal year  $t$ .

The industry-level skewness proxy is ideal for our setting for a number of reasons. First, it is a theoretically justified and easy to obtain proxy of expected skewness (e.g., Hinkley (1975), Conrad, Dittmar, and Ghysels (2013)). Second, as Green and Hwang (2012) show, it is highly correlated with ex post measures of return skewness. Third, on a cognitive level, salience and the availability heuristic (e.g., Kahneman (2011)) support the idea that looking at skewness of returns in an industry in the last year has predictive content for managerial investment decisions. Extreme returns in an industry make this industry salient to CEOs and they will see a project in a more positive light if instances of recent successes of similar projects come to mind easily. Since, by construction, the industry-level skewness measure is high whenever salience is high, it is ideal to capture these heuristic-based effects. Finally, an attractive feature of the measure is that it highlights the importance of the tails of the distribution by focusing on extreme return percentiles. Prior work suggests that it is these tails that are attractive to individuals with a preference for long-shot bets, rather than skewness per se, although the two are highly correlated (e.g., Barberis and Huang (2008), Bali, Cakici, and Whitelaw (2011)).

We show in our robustness section that our results are robust to sensible variations of the skewness measure. There, we also show that using sales growth, or earnings growth, in constructing *Skew*, as accounting-based alternatives to stock returns, yields similar results.

## E. Additional Variables and Data Sources

In our regressions, we control for the standard variables used in the literature. We follow Shin and Stulz (1998) and control for segment and firm cash flows, defined as sum of operating profits and depreciation scaled by total assets. Additionally we control for the median Tobin’s Q in a segment’s FF48-industry and the median Tobin’s Q in the conglomerate’s main FF48-industry. The median is calculated across all standalone firms that operate in the same FF48-industry and Tobin’s Q is defined as  $MVA / (0.9 \times BVA + 0.1 \times MVA)$ , where BVA is the book value of assets and MVA is the market value of assets (common equity plus the book value of assets minus the book value of common equity and balance sheet deferred taxes). It is bounded above at 10 to reduce

the effect of potential measurement error in the book value of assets. We also use size of the firm (segment), defined as the log of firm (segment) sales, age of the firm, defined as log of the current year plus one minus the year in which the firm first appeared in the Compustat database, and the focus of the firm, defined as the ratio of the core (i.e., largest) segment’s sales and the firm’s total sales. We also control for firm skewness, defined as the asset-weighted average skewness across segments in the conglomerate.

To isolate the impact of skewness from the first two moments, we control for segment return and segment volatility. Segment return is defined as the value-weighted monthly rebalanced return in the segment’s FF48-industry, based on all firms with share codes 10 and 11 in CRSP in the same FF48-industry over the 12 months prior to and including the last month of the conglomerate’s fiscal year  $t$ . Segment volatility is defined as the annualized median idiosyncratic volatility in the segment’s FF48-industry, calculated from the residual of a Fama and French (1993) three-factor model estimated on daily data over the same period. We winsorize all continuous variables at the 1% and 99% level.

We use religious affiliation data obtained from the “Churches and Church Membership” files from the American Religion Data Archive (ARDA), state-level lottery sales data from the North American Association of State and Provincial Lotteries (NASPL), county-level demographic data from the U.S. Census, CEO age, compensation, and ownership data from ExecuComp, and the GIM-index data from Andrew Metrick’s website. We document all variables used in our analysis and their definitions in Table A.I in the Internet Appendix.

Table I shows summary statistics of our final sample separately for segments, conglomerates, and standalone firms.

[Insert Table I here]

## II. The Skewness-Investment Relation

### A. Baseline Results

We start by analyzing the relation between skewness and investment using the following baseline regression model:

$$I_{it} = \alpha + \beta_1 Skew_{SEG,it-1} + \beta_2 Skew_{SEG,it-1} \times Small_{SEG,it-1} + \Gamma X_{it-1} + \epsilon_{it}, \quad (4)$$

where, for each segment  $i$ ,  $I_{it}$  is segment-level capital expenditure in fiscal year  $t$  divided by lagged segment assets,  $Skew_{SEG,it-1}$  is expected skewness associated with the segment from equation (3),  $Small_{SEG,it-1}$  is a dummy identifying small segments defined below, and  $X_{it-1}$  is a vector of controls including the small dummy. We run OLS regressions and use standard errors that allow for clustering at the firm level. We include year fixed effects in all regressions, as well as different levels of industry fixed effects.

Table II presents our results. First, specifications (1) and (2) look at the average segment, i.e. we run model (4) without the interaction term. We find that segments with positively skewed expected future returns invest more, statistically significant at the 10% level.

[Insert Table II here]

Our theoretical framework predicts stronger effects in smaller segments, both absolute and relative. We therefore define for each segment  $i$  and fiscal year  $t$  a small segment dummy,  $Small_{SEG,it}$ , equal to one if the segment is both, not in the top-tercile of relative size (measured as segment assets over total conglomerate assets) and not in the top-tercile of segment size across all segments in the sample and fiscal year. Using this definition, about 12,600 segment-year observations (47% of the sample) are classified as small. Those segments invest a total of \$100 billion over our sample period, so they are an economically meaningful subset. We show in the robustness section that our results also obtain when we use only relative size or only absolute size, but combining the two is more powerful.

Column (3) presents results when we run the full model in equation (4). Consistent with both our predictions in Section I.B, we find that the positive skewness-investment relation is much stronger in smaller segments. The coefficient of skewness triples relative to the average firm effect,

and it is now highly statistically significant ( $t = 3.43$ ). This illustrates that the effect on the average segment in specification (2) can be interpreted as a weighted average of the effects on small segments, where the skewness-investment relation is strongly positive, and large segments, where it is indistinguishable from zero. To address concerns that the skewness-small-interaction spuriously picks up other differences between small and large segments, we interact, in specification (4), all control variables with the small segment dummy and obtain similar results for the skewness-investment relation.

Our results obtain after controlling for standard variables. In particular, we control for segment cash flow, and segment investment opportunities proxied for by Tobin's  $Q$ . As expected, segment investment is higher when the segment has higher cash flow and better investment opportunities, consistent with stylized facts in the literature. We also find that older and larger firms, on average, invest less. Because we include segment volatility and return in all regressions, effects are not due to skewness spuriously capturing the first two moments.

The effects we document are economically sizeable. For the average segment, an interquartile range change in skewness leads to a 2.4% change in investment relative to the mean ( $= 4.979 \times 0.038/7.7$ ), based on specification (2). For small segments, the same change in skewness implies a 7.5% change in investment, relative to the mean, based on specification (3). Another way to see that our results are economically important is to compare the skewness effect to the effect of two well-known drivers of investment, namely segment  $Q$  and segment cash flow. For small segments, based on specification (3), the change in investment for an interquartile range change in skewness is more than half that of a comparable interquartile range change in segment  $Q$  (13.6%), and larger than the impact of an interquartile range change in segment cash flow (6.6%).

In sum, conglomerates invest more in segments with high expected skewness. This effect is particularly strong for small segments.

## **B. The Skewness-Investment Relation and Unobservables**

While we control for a number of variables in the above regressions, a potential concern could be that other, potentially unobservable, variables are driving our results. Before addressing this formally, we note that it is not immediately obvious what these unobservables should be, given that we need not only a positive relationship between the omitted variable, investment, and skewness,



but also a negative relationship between this variable and segment size.

A specific concern may be that the skewness-investment relation might be driven by unobservable time-varying factors on the industry level. We investigate this possibility by using industry-adjusted investment (e.g., Lamont (1997)) as dependent variable in specifications (5) to (7) of Table II. To control for common shocks to investment in an industry in a given year, for example technology or regulatory shocks, we subtract the mean asset weighted investment across all standalone companies in the same FF48-industry from the segment investment variable used in specifications (1) to (4). (Implicitly, this specification compares conglomerate segments to standalone companies; an issue we investigate further below.) Columns (5) to (7) document that the skewness-investment relation is robust. The effect on the average segment becomes economically and statistically more significant ( $t$ -statistic = 2.63). The skewness-investment relation for small segments continues to be highly significant.

We seek to further minimize concerns about unobservables in Table III. We show results both for the average segment (Panel A), and the specification with the interaction term that allows us to isolate the impact on small segments (Panel B). As before, we expect more pronounced results for smaller segments. Control variables are the same as those in Table II.

[Insert Table III here]

First, we follow Rajan, Servaes, and Zingales (2000) and adjust industry-adjusted segment investment by subtracting the asset weighted average industry-adjusted segment investment across all the segments of the conglomerate firm. This firm-industry-adjusted investment measure accounts for the fact that conglomerates might be able to raise more cash than standalones. Therefore, conglomerates might invest more in *all* segments. Specification (1) in Table III suggests that the documented relation between skewness and investment is not spuriously induced by a tendency of conglomerates to invest more across the board. As was the case for the industry-adjusted measure, the skewness-investment relation is highly statistically significant also for the average segment ( $t$ -statistic = 2.99).

Gormley and Matsa (2014) point out that standard industry-adjustments can lead to biased coefficients. Specification (2) shows that our results are unaffected when we include industry-year fixed effects instead of using industry adjustments, which follows a prescription by those

authors.<sup>5</sup> Coefficients on our variables of interest are very similar to what we found using the industry-adjusted and firm-industry-adjusted investment variables, indicating that potential biases induced by industry-adjusted variables are not a big concern in our setting. In sum, then, Table II (specifications (5) to (7)) and Table III specifications (1) and (2) suggest that time-varying industry-level unobservables are not inducing our results.

Another concern might be that there are firm or segment level unobservables. We present three approaches to address this in specifications (3) to (5). First, we regress the year-to-year change of segment investment on the year-to-year change in skewness and the control variables. Second, we include conglomerate fixed effects. Lastly, we control for segment fixed effects. These tests are demanding on the data, because investment levels are on average quite sticky. The results in specifications (3) to (5) are nevertheless reassuring. While we lose significance on the average segments, our findings on the small segments remain intact, which is exactly where we expect to find a more pronounced skewness-investment relation. Under the hypothesis that the effects are due to the CEO long shot bias, one way to interpret these findings is that CEOs invest more in small long shot segments when recent successes in similar projects become more salient. We conclude that higher investment in small segments with high expected skewness cannot be explained by unobservable time-invariant heterogeneity on the firm or segment level.

### C. Robustness

For robustness, we estimate alternative versions of specifications (2) and (3) in Table II. Results are shown in Table IV. We first alter the calculation of the industry-level skewness measure. Specifically, replacing the 1st percentile by the 5th percentile in the definition of the skewness measure in equation (3), using earnings growth or sales growth as accounting-based alternatives to stock returns in computing the skewness measure, or using the MAX measure by Bali, Cakici, and Whitelaw (2011) instead of the skewness measure, yields similar results (specifications (1) to (4)). To minimize concerns that skewness is a proxy for local investment opportunities, we estimate a MSA-specific skewness measure which, for each conglomerate, is computed as in equation (3), but after excluding all industry peers from that MSA. The results are hardly affected (specification (5)).

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<sup>5</sup>We can include industry-fiscal year effects in our regression because we estimate skewness over the twelve months preceding each firm’s fiscal year end, and because fiscal year ends vary across firms.

[Insert Table IV here]

Specifications (6) and (7) define small segments using absolute size and relative size as an alternative to the small dummy in our baseline regressions, which combines absolute and relative size attributes. Results show that using the inverse of relative size or the inverse of absolute size instead of the small dummy yields results consistent with our baseline.

We perform additional robustness checks, which, for brevity we relegate to the internet appendix. As an alternative to the Fama-French industry classification we use the Hoberg-Phillips 100 industry classification (Hoberg and Phillips ((2010a), (2010b))), and find results are robust. We find similar results as in our baseline when we control for co-skewness, which indicates that our results are not due to the skewness CAPM. We control for new economy status and we drop very small segments with assets under \$10 million, without affecting our results.

We show that the vega of the CEO pay package – the value change of the CEO option package for a change in the riskiness of the firm – and a proxy for overconfidence based on executive stock option holdings does not explain our results. We control for CEO age and tenure in these tests. Although we lose more than 60% of our sample because of data availability, results show that the skewness-investment relation is neither induced by risk-taking incentives from pay packages, nor capturing effects related to standard proxies for overconfidence. The point estimates on our variables of interest are essentially unchanged relative to our baseline. The latter test is interesting because overconfidence could be another driver of the long shot bias if we assume that managers are systematically more overconfident about high skewness projects. Hence, we do not find empirical evidence to support overconfidence as a strong driver of the long shot bias.

Kruger, Landier, and Thesmar (2015) propose that firms overinvest into high beta segments because they use one overall beta to evaluate investment projects. We include segment betas computed following their approach. All our results are unaffected, which shows that we are capturing a different effect.

Overall, we conclude that our results are robust to a number of plausible alterations of our baseline setup.

## D. Comparing Conglomerates to Standalone Firms

The evidence so far shows that conglomerates invest more into skewed segments than can be explained by standard determinants of investment levels. An alternative test to show that investment in skewed segments is particularly high is to compare conglomerate segments with otherwise comparable standalone firms.

To implement this test, we follow the matching procedure proposed in Ozbas and Scharfstein (2010). Specifically, we match a conglomerate segments to a standalone firm by industry, year, size, and firm age. Whenever there are multiple possible matches – which only occurs for the industry-year match – we randomly assign a match based on the firm name. We then run:

$$\Delta I = \alpha + \beta_1 Skew_{SEG} + \beta_2 Q_{SEG} + \beta_3 \times \Delta CashFlow + \epsilon, \quad (5)$$

that is we relate the difference in investment levels between segment and standalone, denoted by  $\Delta I$ , to the skewness of the industry. Our prediction is that  $\beta_1$  is positive, which indicates that the difference in investment levels between segments and standalones increases with industry skewness. The constant in the regression controls for average differences in investment across segments and matched firms, which might result, for example, from greater external debt-capacity due to the conglomerate structure. We also include Tobin’s Q and the difference in cash flow levels because these variables have been shown to predict differences in investment levels by Ozbas and Scharfstein (2010).

Table V presents results. Looking at the top panel, we find that the coefficient on skewness is positive and significant, which indicates that investment levels of conglomerate segments are particularly high relative to standalone firms for segments in industries with high expected skewness. This is true for four different procedures to find a match, including matches by (i) industry and year, (ii) industry, year and size (iii) industry, year, and size, provided that the size of the potential match is within 20% of the segment size, and (iv) industry, year, size, and firm age. Since we control for Q and cash flow differences, the results cannot be explained by differences in investment opportunities, or cash flow available at the segment level.

[Insert Table V here]

These patterns are consistent with overinvestment of conglomerates in segments with high expected skewness, a practice that could be facilitated by the ability of management to redistribute capital across segments. The evidence complements our regression evidence using industry-adjusted variables in Table II and III. A possible alternative view would hold that standalone firms underinvest in these industries. While we note that it does not seem obvious why this would be the case, given that we are already controlling for differences in access to capital, we propose a simple test to rule out this alternative explanation. Our argument is based on relative segment size. If the patterns are due to overinvestment in conglomerates, then the effects should be more pronounced for relatively small segments, because it is easier for conglomerates to meaningfully alter investment budgets through reallocating resources across segments if the segment is small and the rest of the firm – and therefore the resources to be reallocated – are large, and because of the reasons in Section I.B which suggest the CEO long shot bias matters more in relatively smaller segments. By contrast, if effects are due to underinvestment in standalones, the *relative* size of the matched segment should not matter.

The bottom two panels of Table V show that the effects are concentrated among matches of single-segment firms with segments that are relatively small within their conglomerate. Across all matching strategies, the coefficients are higher than in the baseline case and statistical significance remains high. The effects are not present when we look at the subset of relatively large segments. Note that the constant in these regressions picks up all stable differences across conglomerates and standalones. So even if there were differences in access to external funding across small and large segments in absolute terms, and even if the relative size match would not completely eliminate the relation to absolute size, such differences cannot easily explain why we see larger investment differences, because those would be captured by the constant.

## E. Value Implications

The above results show that conglomerates invest more in skewed segments than standalones. In this section we look at valuation implications to get further insight into the underlying motivation. Three scenarios are possible. First, higher investment in skewed segments could reflect optimal investment behavior. For example, it might be a positive signal about the ability of conglomerates to exploit good investment opportunities. In this case, conglomerates with skewed segments would

on average trade at a premium. Second, higher investment in skewed segments could have no value effect in equilibrium. Lastly, higher investment in skewed segments could be suboptimal. This would be consistent with conglomerate firms inefficiently allocating resources to segments with high expected skewness. In this case, conglomerates with high skewness segments would on average be valued at a discount.

To test this formally, we augment standard diversification discount regressions with a term measuring the incremental discount for conglomerates with skewed segments. Following Berger and Ofek (1995) we compute a measure of excess value, defined as the log difference between market value and imputed value of the conglomerate. Imputed value of a conglomerate is the sum of the individual segment values estimated by using FF48-industry sales multipliers. We then regress this excess value on a dummy that is one for conglomerates and a large set of control variables used in Campa and Kedia (2002). To measure the impact of segment skewness on conglomerate value, we add a dummy variable, *Skewed*, that is one if, in a given year, the conglomerate has a segment operating in an industry with above median expected skewness, which is outside the conglomerate's major FF12-industry. The latter condition allows us to focus on smaller segments, which is where we expect more pronounced effects.

Table VI presents results. We first run standard OLS regressions. Consistent with the existing literature on the diversification discount we find that conglomerates trade on average at a discount of about 10% to 11%. More interestingly, the significant negative coefficient on *Skewed* indicates that conglomerates that have at least one non-core segment operating in an industry with high expected skewness trades at a discount that is another 4.2 to 4.5 percentage points larger. Hence, such multi-segment firms trade at a discount relative to other multi-segment firms without skewed segments, and relative to otherwise similar standalone firms. This is exactly what we would expect to see if capital was inefficiently allocated to skewed segments in conglomerates.

[Insert Table VI here]

A common concern with this type of regressions is endogeneity because the decision to diversify might itself be endogenous. Note first that this may be irrelevant for our finding that conglomerates with skewed segments trade lower than other conglomerates since the endogeneity-induced bias would affect both variables, *Conglomerate* and *Skewed*, in the same way. To deal with this

endogeneity problem more formally, we follow Campa and Kedia (2002) and use three different approaches. We first add firm fixed effects to our regressions. If the decision to diversify is driven mainly by time-invariant factors on the firm level, then the fixed effects will eliminate the source of endogeneity. As shown in columns (3) and (4) of Table VI, including the fixed effects does not alter our main conclusions. Both, the diversification discount and the incremental discount due to the presence of a skewed non-core segment are somewhat attenuated but remain statistically and economically significant. In particular, we continue to find a sizeable detrimental effect on firm value from having a skewed segment of 18% to 23% relative to other conglomerates.

We also use an instrument and a Heckman selection model to minimize endogeneity concerns. Campa and Kedia (2002) argue that the fraction of firms in an industry that are diversified is a valid instrument. The instrument has been subsequently used in the literature (e.g., Kuppuswamy and Villalonga (2010)). We use it in our tests as well. A specific feature of our setting is that if the diversification dummy is endogenous, then, since *Skewed* can only take the value of one for conglomerates, it is necessarily correlated with the diversification dummy and hence also endogenous. To the extent that *Skewed* is itself not endogenous, we can legitimately instrument it with the interaction of the instrument for the diversification dummy and *Skewed* to address the endogeneity problem (Angrist and Pischke (2008)). To show the strength of our instruments, we report *p*-values for the Angrist and Pischke (2008) F-test for weak instruments.

Consistent with the diversification discount literature, we find that using IV and Selection methods affects the estimates of the diversification discount dummy (*Conglomerate*) substantially. Important in our setting is the coefficient on *Skewed*. The results in Table VI show that controlling for endogeneity reinforces our previous results that conglomerates with a segment operating in a high skewness industry are valued at a discount. Across specifications (5) to (8), this discount relative to standalone firms is between 8.5% to 13%, which is economically large. The difference to standalones is highly significant statistically. So is the difference to conglomerates without skewed segments. The Angrist-Pischke F-test suggests that weak instruments are not a concern.

In the Internet Appendix we present a range of alternative specifications. Results are very similar when we use the number of segments with above median skewness as an alternative to the dummy *Skewed*. We also find similar results when we repeat the analysis using the Hoberg-Phillips 100 industry classification instead of the FF48-industries. We also replace *Skewed* by the

asset-weighted average skewness of all small segments in a conglomerate-year, and find our results are robust. Finally, a potential concern could be that *Skewed* is correlated with the diversity of a company’s operations and therefore reflects a diversity discount as in Rajan, Servaes, and Zingales (2000) and Lamont and Polk (2002). Consistent with their results, we find a negative effect of their respective diversity measures on conglomerate valuation when we include them alongside our *Skewed* variable. The results for *Skewed*, however, are essentially unchanged.

Overall, the results in this sections are consistent with the hypothesis that overinvestment in skewed segments is detrimental to shareholder wealth.

### III. Investment and the CEO Long Shot Bias

In this section, we present evidence for a behavioral explanation for the skewness-investment relation documented above: CEOs subject to the long shot bias overinvest in projects with high expected skewness, such as project B in the example in the introduction. This will adversely affect shareholder wealth if the skewed project is favored over a non-skewed project with lower NPV. We discuss potential alternative explanations in Section IV.

#### A. Evidence from a Geographical Gambling Proxy

A clean test of the hypothesis that the skewness-investment relation documented in the previous section is driven by a long shot bias of CEOs would exploit exogenous variation in the intensity of the bias, and then show that the investment in skewed segments is most pronounced where the bias is strongest. The aim of this section is to provide such a test. We draw on recent work by Kumar, Page, and Spalt (2011) to identify exogenous variation in how much CEOs like long shots. Specifically, those authors propose using CPRATIO as a variable that captures gambling propensity of decision makers in a geographical area. CPRATIO is the ratio of Catholics to Protestants as a percentage of the total population in a county. This measure is motivated by the observation that Catholic teachings are more lenient towards gambling than Protestant teachings and that religious background, specifically the difference between Catholics and Protestants, is well-established as a key predictor of gambling behavior in the empirical gambling literature (e.g., Berry and Berry (1990), Martin and Yandle (1990), Ellison and Nybroten (1999), Diaz (2000), and Hoffman (2000)).



Kumar, Page, and Spalt (2011) show that decision makers in regions with higher CPRATIO are more likely to take long shot bets in different contexts, including buying lottery tickets, stock market investment, and corporate decisions. Benjamin, Choi, and Fisher (2015) provide experimental support for the CPRATIO measure.<sup>6</sup>

Our empirical strategy is to assign each conglomerate to a county by headquarter – since this is where the CEO is – and then to assign to each firm the CPRATIO of this county. We posit that decisions made by CEOs are not orthogonal to the religion-induced local gambling norms. For example, decisions of a manager in Salt Lake City would be influenced at least to some degree by the local Mormon culture (even if the manager is not a Mormon). We then re-run our baseline regressions for the subsample of high and low CPRATIO firms defined as firms located in counties with above median CPRATIO in a given year. We follow Kumar, Page, and Spalt (2011) in constructing the variable and refer the reader to their paper for details.

Table VII presents results consistent with the long shot hypothesis. We find for the average segment in Panel A that in low CPRATIO counties, which is where gambling and skewness in returns are less attractive, our effects become severely attenuated and, although they keep the right sign, become insignificant. By contrast, effects in high CPRATIO counties are large. Coefficients are more than ten times as large and statistically significant. In Panel B, we present again results that separate between large and small segments. We find the effect is mostly concentrated in small segments in high CPRATIO areas. For those segments, coefficients are more than five times larger than coefficients for small segments in low CPRATIO counties. Wald tests indicate that the coefficient on the small segment-skewness interaction term is statistically different across the subsamples at the 5% level.

[Insert Table VII here]

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<sup>6</sup>The gambling views typical of many Protestant churches are expressed in the United Methodist Church’s 2004 Book of Resolutions: “Gambling is a menace to society, deadly to the best interests of moral, social, economic, and spiritual life, and destructive of good government. As an act of faith and concern, Christians should abstain from gambling [...]” The position of the Catholic Church on gambling is summarized in The Catechism of the Catholic Church (#2413): “Games of chance (card games, etc.) or wagers are not in themselves contrary to justice. They become morally unacceptable when they deprive someone of what is necessary to provide for his needs and those of others. [...] Unfair wagers and cheating at games constitute grave matter, unless the damage inflicted is so slight that the one who suffers it cannot reasonably consider it significant.” Overall, Catholics are more tolerant towards gambling, and a sizeable literature provides consistent empirical evidence (e.g., Brenner and Brenner (1990), Mikesell (1994) and Kumar (2009)). See, for example, Thompson ((2001), Pages 317-324) for a summary of the gambling views of major religious denominations in the U.S. Barberis (2013) discusses how CPRATIO can help understand preferences for tail risks in finance and economics, more broadly.

Since we are including industry fixed effects for each segment in our regressions, geographical industry clustering cannot explain our findings. Moreover, our findings are not driven by the fact that some of the largest cities in the US, like New York, Boston, or Los Angeles are in regions with high CPRATIO. When we include a dummy that is one if the firm is located in one of the ten largest MSAs by population (New York, Los Angeles, Chicago, Miami, Philadelphia, Dallas, Boston, San Francisco, Detroit, and Houston) our results are essentially unchanged. Our results are also not driven by a number of county level variables that might be correlated with the local religion such as education, age, the fraction of minority residents, the total county population, the male-to-female ratio, the fraction of residents living in urban areas, and the fraction of married households. Lastly, we are not capturing effects related to states or state policies as we find similar patterns when we analyze within-state variation.

Overall, the CPRATIO results provide strong support for our hypothesis that CEOs subject to the long shot bias tilt capital allocations towards segments with high skewness. It also lends support to our implicit assumption that decision-making at the headquarter level is responsible for the investment patterns, since we match firms to CPRATIOs by headquarter location, and since the actual segments may be located somewhere else. This test allows us to discriminate the CEO long shot bias from potentially plausible alternative explanations, including agency problems, career concerns, and risk-taking induced by pay packages. While differences in Catholic and Protestant beliefs and actions when it comes to long shot preferences have been amply documented, it is not obvious why agency, career concerns, or inefficiencies in pay should be more of an issue for otherwise similar firms in Catholic counties than in Protestant counties.

## **B. Additional Evidence from Subsamples**

This section provides five additional tests to support our conjecture that the CEO long shot bias leads to overinvestment in skewed segments. The first two tests investigate further if our patterns are related to betting on long shots, while the remaining three focus on the role of managerial discretion. Our approach is to estimate our benchmark specifications (Table II, columns (2) and (3)) in subsamples. All results in this section are shown in Table VIII, where for conciseness, we report only the two skewness coefficients of interest, namely the skewness variable and its interaction with segment size.

[Insert Table VIII here]

First, we use actual state-level lottery ticket sales data obtained from the North American Association of State and Provincial Lotteries (NASPL). This data covers 42 states as well as Washington D.C. and Puerto Rico over the period 1990 to 2007. Because this data captures only part of the gambling opportunities for individuals in a state, and because lottery existence and features vary across states, we focus on the year-to-year change in lottery expenditure. To the extent that data coverage and lottery design does not vary much over time within a state, the change in lottery sales should provide a reasonably clean way to identify times of temporarily increased local gambling appetite. We again match firms to states by headquarter location and then split the sample into firms located in states with high and low changes in annual per capita lottery sales. The top panel in Table VIII shows that, despite our sample shrinking by half due to data availability, our skewness-related effects in conglomerate investment are particularly pronounced for firms in regions and times where local gambling propensity is high. This is in line with the view that CEOs are influenced by local gambling attitudes and that these gambling attitudes translate into higher investment for skewed segments.

Next, we investigate a potentially important CEO attribute directly. Specifically, we conjecture that younger CEOs would be more aggressive in their investment behavior and more likely to take a long shot. This conjecture is supported by prior work documenting that preference for skewness in investment returns tends to decrease with age (e.g., List (2003), Goetzmann and Kumar (2008), Kumar (2009)). Because we obtain CEO age from the ExecuComp database, we lose more than 70% of our sample in this test, relative to the benchmark in Table II, which affects statistical significance of our estimates. Still, the effect from comparing the oldest CEOs (upper tercile in a given year) to the youngest CEOs is striking. While the point estimates of our coefficients for young CEOs are much higher than those of the benchmark model in Table II, the effects are much weaker for older CEOs (Table VIII, Panel B). This is consistent with higher gambling propensity of young CEOs.

Although CEOs have considerable authority in capital allocation decisions, constraints on managerial discretion limit the ability of CEOs to defend a capital allocation that overinvests into skewed segments. It will be easier for CEOs to impound their preferences on capital allocations if they are more powerful. We therefore split the sample into firms with high and low managerial

power measured by the Gompers, Ishii, and Metrick (2003) index. We can get the GIM-index only for a subset of firms. As shown in Table VIII, Panel C, we nevertheless find that our effects are more pronounced in corporations which Gompers, Ishii, and Metrick (2003) label “dictatorships”.

The next set of tests in Panel D shows that CEOs with more equity ownership, who we expect to be more powerful in their firms, are associated with more pronounced effects. This is again consistent with the idea that CEOs with more discretion find it easier to go with their guts. (We comment further on the ownership results below.) Finally, we use CEO tenure as an additional proxy for CEO power. The regressions in Panel E shows that the skewness-investment relation is related to tenure. We obtain a coefficient on the interaction term of 28.75 ( $t = 2.15$ ) for CEOs with long tenure but only 3.60 ( $t = 0.32$ ) for CEOs with short tenure. Even though we again lose many observations due to data availability, the evidence suggests clearly that CEOs with longer tenures, who plausibly are more powerful in their organizations, are more likely to exhibit a long shot bias when allocating resources.

Individually, the tests in this section may not be as sharp as the CPRATIO test and the difference between the subsamples is in many cases statistically insignificant, presumably because we lose a large part of our sample in each test. However, the CEO long shot hypothesis provides a unifying explanation for these results, while it seems hard to think of an alternative hypothesis that would collectively explain them. Therefore, in sum, we view these tests as very informative.

## IV. Alternative Explanations and Discussion

### A. Agency Problems

In the presence of agency problems, CEOs can strategically exploit subjectivity in valuation assumptions to tilt capital budgets towards an allocation that maximizes private benefits. Conceptually, the main difference between the long shot bias and a standard agency model is that, in the agency framework, the CEO knows she is not maximizing firm value. She consciously trades-off private benefits for shareholder value. By contrast, a CEO subject to the long shot bias may actually try to maximize shareholder value, but fail because the bias is subconscious (a “gut feeling”).

One common implication of agency models is that resource allocation tends to be “socialistic” – meaning that weak segments (usually measured by Tobin’s Q) are able to get more of the corporate

budget than they otherwise would. However, our results are not related to weak segments in the way agency theory would predict. Tobin’s  $Q$  for skewed segments is on average *higher* than Tobin’s  $Q$  for other segments (1.48 vs. 1.29). Moreover, we control for segment fixed effects in Table III, so the skewness-investment relation cannot be explained by corporate socialism as long as the differences in bargaining power between segments is relatively stable, which appears plausible.

While this already casts doubt on whether the skewness-investment relation can be explained by appealing to agency problems, we provide an additional test. The canonical way to address the principal-agent problem is granting equity-based compensation (e.g., Jensen and Meckling (1976)). Under the null that the relation is driven by agency problems, using the same logic as a recent related paper by Ozbas and Scharfstein (2010), we should therefore observe a weaker skewness-investment relation when managers have more skin in the game via their compensation contracts. Panel D in Table VIII shows that we do not find support for this in the data when we split the sample by CEO stock ownership (computed as in Ozbas and Scharfstein (2010)). If anything, we find that effects are actually stronger when managers have high ownership and weaker when ownership is low. This implies skewness affects investment less when agency problems are likely to be more severe. We therefore conclude that a standard agency setting with efficient contracting in which CEOs knowingly distort investment to maximize private benefits does not explain the skewness-investment relation.

It may be useful to point out the relation of the ownership test to the GIM test in Table VIII. There we have conjectured that powerful CEOs in “dictatorship” firms would find it easier to go with their guts in making investment decisions. An alternative, agency-based, view would hold that agency problems are more acute in “dictatorship” firms. Hence, the GIM test cannot be used to separate an agency-based explanation from the long shot bias explanation. The ownership test is particularly informative because low ownership is correlated positively with the presence of agency problems. By contrast, it appears implausible to think that CEOs with low ownership are more powerful inside their organization. In fact, there is reason to conjecture the opposite. First, CEOs with higher ownership are more likely to have performed well in the past and to be with the firm for a longer time, both of which would be positively correlated with the standing of a CEO inside the firm. Second, managerial power may actually lead to higher pay (e.g., Bebchuk and Fried (2004)).

The ownership test is therefore valuable in two respects: it shows that the skewness-investment

relation is not a standard agency issue, and highlights the potential importance of CEO power in transmitting biases into decisions. It also emphasizes an important difference between agency and managerial biases: since biases operate subconsciously, granting equity-linked pay may have little bite, because CEOs already *think* they are maximizing shareholder value – even though they are not.

## B. Skewness as a Proxy for Good Investment Opportunities

Prior research has documented that CEOs of conglomerates can in some situations have an advantage in identifying and exploiting good investment opportunities (“winner-picking”), which creates value (e.g., Stein (1997), Maksimovic and Phillips (2002)). Table VI strongly suggests that the skewness-investment relation is not related to winner-picking, since we see additional valuation discounts in conglomerates with skewed segments. Similarly, our sample split results from the previous section are not predicted in any obvious way by differences in investment opportunities. Moreover, industry-level variation in investment opportunities cannot easily explain our results given our industry-adjusted investment measures and industry-year fixed effects we used in Table II and III. Still, to be conservative, we run additional tests to rule out that we observe high investment in segments with high expected skewness because skewness proxies for investment opportunities.

First, as a direct test we include additional controls for investment opportunities in our baseline regressions. We follow Shin and Stulz (1998) and include segment sales growth and R&D. We also control for employment growth and worker productivity (sales per employee) as those variables may also be correlated with future investment opportunities. Note that we are already controlling for Tobin’s Q of segment and core segment, and also include industry fixed effects. Panel A in Table IX shows that our results are not affected, and if anything get stronger when we control for these variables.

[Insert Table IX here]

As a second test, we look again at investment in standalone companies.<sup>7</sup> If the skewness measure is a proxy for good investment opportunities it should predict investment for standalone firms just as it does predict investment for conglomerates. The results in Table IX, Panel B, show that

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<sup>7</sup>We thank Malcolm Baker for suggesting this test.

this is not the case. The skewness-investment relation for standalones is rather weak already in specification (1), and breaks down completely once we control for industry or firm fixed effects. That is, even if skewness were a proxy for good investment opportunities it would not have any incremental explanatory power over and above what is captured by industry and firm fixed effects. By contrast, Tobin’s Q – a standard proxy for investment opportunities – is a strong predictor of investment even if we control for industry or firm fixed effects. In sum, both tests in this section suggest that skewness is not simply proxying for good investment opportunities.

Some comments are in order. First, cash constraints for standalones cannot easily explain why skewness is not related to investment, because we still see a strong effect for Tobin’s Q.<sup>8</sup> Second, the absence of a skewness-investment relation for standalones may support an argument in Stein (1997) who suggests that a CEO will be more likely to do a good job of winner-picking when the firm operates in related lines of business. Because assessing relative value may be easier when comparing projects in related lines of business, and because a bias may affect projects in related lines of business similarly, the CEO long shot bias may be more likely to distort capital budgets in conglomerates. Third, while both conglomerate and standalone CEOs can reallocate capital across projects – which is why the CEO long shot bias may well matter *inside* standalone firms – only the conglomerate CEO can reallocate capital across segments operating in different industries. This additional channel may amplify the impact of the CEO long shot bias in conglomerates.

Finally, investment in skewed segments could be one way to change the direction of the firm by diversifying into a new line of business (e.g., Matsusaka (2001)). While this alternative theory is conceptually reasonable, we find little support for it explaining the skewness-investment relation in the data (results unreported). In particular, conglomerates are not more likely to venture into a new industry if skewness in this industry is high, and we find firms investing in a small skewed segment today have a *smaller* likelihood of making this business their core activity over the next 15 years. If small skewed segments would be promising nuclei for new directions of the firm, we would expect to find the opposite.

In sum, the skewness-investment relation is not due to skewness proxying for investment opportunities.

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<sup>8</sup>We have run additional tests using the Kaplan and Zingales (1997) index but did not find evidence in favor of cash constraints mattering for the lack of a skewness-investment relation for standalones.

### C. Skewness as a Proxy for Risk and Uncertainty

A final concern might be that our findings are really about risk or uncertainty *per se*, which skewness is a proxy for. In this section we examine three ways in which uncertainty could potentially influence investment levels. First, in a real options setting, higher uncertainty might make an investment project more valuable. Second, more uncertainty could lead CEOs to simply make more mistakes when allocating capital. Third, as in Pastor and Veronesi ((2003), (2006)), higher uncertainty about growth rates can lead to rationally higher valuations because of Jensen’s inequality.

Standard real option models cannot easily explain our results as higher uncertainty makes the option to delay more valuable. This would lead to lower and not higher investment levels (e.g., Eisdorfer (2008)). To address the remaining two explanations we first note that we control for idiosyncratic volatility (and its interaction with segment size) in all our tests, which makes an explanation based on risk and uncertainty unlikely.

As a second test, we follow Green and Hwang (2012) and split the skewness measure in equation (1) into left-skew and right-skew. Right-skew is defined as  $(P_{99} - P_{50})$  and left-skew is defined as  $(P_{50} - P_1)$ . Table X present results. As expected, investment is higher when right-skew is higher. Importantly, investment is lower when left-skew is larger. This suggests that it is the long shot property of a segment, i.e., the combination of large right-skew and small left-skew, that is driving investment. It is not risk or uncertainty *per se* because then we would expect to see higher investment also for projects with more left-skew. These results also show that we are not simply capturing effects related to hard-to-value projects.

[Insert Table X here]

Finally, and in addition to the above arguments, we note that any alternative hypothesis for our results based on rationally higher investment in risky, uncertain, environments faces the difficulty of explaining (i) why we see valuation discounts, (ii) why results should depend on CPRATIO, and (iii) why the skewness-investment relation is absent for standalone firms. Overall, we conclude that our findings are not a result of skewness proxying for risk or uncertainty.



## V. Conclusion

This paper documents that segment-level investment in conglomerates increases with the expected skewness of the segment. The patterns are not explained by established determinants of internal capital allocation and unlikely to be caused by unobservables on the industry, firm, or segment level. Conglomerates invest more in segments with high skewness than otherwise similar standalone firms and there are substantial valuation discounts for conglomerates with skewed segments relative to other conglomerates and relative to standalone firms.

We find little support in the data for explanations based on investment opportunities, agency problems, or uncertainty. The evidence is most consistent with what we label the “CEO long shot bias”. CEOs subject to the long shot bias in conglomerate firms use their decision making authority to channel funds to segments with higher skewness *because* these segments offer a small chance of a large payoff. Potential underlying drivers of this phenomenon include probability weighting in prospect theory, anticipation utility, or the availability heuristic. The CEO long shot bias thus has broad support from decision sciences and is also consistent with survey evidence suggesting that CEOs rely to a considerable degree on “gut feel” when making internal capital allocation decisions. Using an exogenous measure of local gambling propensity, we show that the skewness-investment relation is particularly pronounced when CEOs are likely to find long shots attractive.

In sum, we argue that the special authority of CEOs in capital allocation decisions, and the fact that assumptions in valuation models are partly subjective, make it possible for the CEO long shot bias to affect capital budgeting. Providing further evidence using project-level data, and investigating in greater detail to what extent internal capital markets amplify the bias, may be promising directions for future research. The broader implication of our work is that corporate investment is affected by CEO biases. How important the resulting inefficiencies in capital allocations are for the economy as a whole is an important question for future research.

## References

- Angrist, Joshua, and Joern-Steffen Pischke, 2008, *Mostly Harmless Econometrics* (Princeton University Press).
- Baker, Malcolm, and Jeffrey Wurgler, 2011, Behavioral corporate finance: A survey, *NBER Working Paper Series*, No. 17333 August.
- Bali, Turan G., Nusret Cakici, and Robert Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.
- Barberis, Nicholas, 2012, A model of casino gambling, *Management Science* 58, 35–51.
- , 2013, The psychology of tail events: Progress and challenges, *The American Economic Review* 103, 611–616.
- , and Ming Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices, *American Economic Review* 98, 2066–2100.
- Bebchuk, Lucian, and Jesse Fried, 2004, *Pay without performance: the unfulfilled promise of executive compensation* (Harvard University Press).
- Benjamin, Daniel J., James J. Choi, and Geoffrey Fisher, 2015, Religious identity and economic behavior, Working Paper, Yale University.
- Berger, Philip G., and Eli Ofek, 1995, Diversification’s effect on firm value, *Journal of Financial Economics* 37, 39–65.
- Berry, Frances S., and William D. Berry, 1990, State lottery adoptions as policy innovations: An event history analysis, *American Political Science Review* 84, 395–415.
- Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2012, Salience theory of choice under risk, *The Quarterly Journal of Economics* 127, 1243–1285.
- Boyer, Brian, Todd Mitton, and Keith Vorkink, 2010, Expected idiosyncratic skewness, *Review of Financial Studies* 23, 169–202.
- Brenner, Reuven, and Gabrielle A. Brenner, 1990, *Gambling and Speculation* (Cambridge University Press, Cambridge, UK).
- Brunnermeier, Markus K., and Jonathan A. Parker, 2005, Optimal expectations, *American Economic Review* 95, 1092–1118.
- Campa, Jose Manuel, and Simi Kedia, 2002, Explaining the diversification discount, *Journal of Finance* 57, 1731–1762.
- Chava, Sudheer, and Amiyatosh K. Purnanandam, 2010, CEOs vs. CFOs: Incentives and corporate policies, *Journal of Financial Economics* 97, 263–278 forthcoming.
- Conrad, Jennifer, Robert F Dittmar, and Eric Ghysels, 2013, Ex ante skewness and expected stock returns, *Journal of Finance* 68, 85–124.
- de Athayde, Gustavo M, and Renato G Flôres Jr, 2004, Finding a maximum skewness portfolio: a general solution to three-moments portfolio choice, *Journal of Economic Dynamics and Control* 28, 1335–1352.

- Diaz, Joseph D., 2000, Religion and gambling in sin-city: A statistical analysis of the relationship between religion and gambling patterns in Las Vegas residents, *Social Science Journal* 37, 3.
- Eisdorfer, Assaf, 2008, Empirical evidence of risk shifting and asset substitution in financially distressed firms, *Journal of Finance* 63, 609–637.
- Ellison, Christopher G., and Kathleen A. Nybroten, 1999, Conservative protestantism and opposition to state-sponsored lotteries: Evidence from the 1997 Texas poll, *Social Science Quarterly* 80, 356–369.
- Fehr-Duda, Helga, and Thomas Epper, 2012, Probability and risk: Foundations and economic implications of probability-dependent risk preferences, *Annual Review of Economics* 4, 567–593.
- Friedman, Milton, and Leonard J. Savage, 1948, The utility analysis of choices involving risk, *Journal of Political Economy* 56, 279–304.
- Goetzmann, William N., and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.
- Gompers, Paul, Joy Ishii, and Andrew Metrick, 2003, Corporate governance and equity prices, *The Quarterly Journal of Economics* 118, 107–155.
- Gormley, Todd A, and David A Matsa, 2014, Common errors: How to (and not to) control for unobserved heterogeneity, *Review of Financial Studies* 27, 617–661.
- Graham, John R., Campbell R. Harvey, and Manju Puri, 2015, Capital Allocation and Delegation of Decision-Making Authority Within Firms, *Journal of Financial Economics* 115, 449–470.
- Green, T. Clifton, and Byoung-Hyoun Hwang, 2012, IPOs as lotteries: Expected skewness and first-day returns, *Management Science* 58, 432–444.
- Harvey, Campbell R, John C Liechty, Merrill W Liechty, and Peter Müller, 2010, Portfolio selection with higher moments, *Quantitative Finance* 10, 469–485.
- Hinkley, David V, 1975, On power transformations to symmetry, *Biometrika* 62, 101–111.
- Hirshleifer, David A., Angie Low, and Siew Hong Teoh, 2012, Are overconfident CEOs better innovators?, *Journal of Finance* 47, 1457–1498.
- Hoberg, Gerard, and Gordon Phillips, 2010a, Product market synergies and competition in mergers and acquisitions: A text-based analysis, *Review of Financial Studies* 23, 3773–3811.
- , 2010b, Text-based network industries and endogenous product differentiation, Working Paper, University of Maryland.
- Hoffman, John P., 2000, Religion and problem gambling in the U.S., *Review of Religious Research* 41, 488–509.
- Jensen, Michael C., and William H. Meckling, 1976, Theory of the firm: Managerial behavior, agency costs and ownership structure, *Journal of Financial Economics* 3, 305–360.
- Jouini, Elyès, Paul Karehnke, and Clotilde Napp, 2014, On portfolio choice with savoring and disappointment, *Management Science* 60, 796–804.

- Kachelmeier, Steven J., and Mohamed Shehata, 1992, Examining risk preferences under high monetary incentives: Experimental evidence from the people's republic of china, *The American Economic Review* 82, pp. 1120–1141.
- Kahneman, Daniel, 2011, *Thinking, Fast and Slow* (Macmillan).
- , and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–291.
- Kaplan, Steven N, and Luigi Zingales, 1997, Do investment-cash flow sensitivities provide useful measures of financing constraints?, *Quarterly Journal of Economics* 112, 169–215.
- Kruger, Philipp, Augustin Landier, and David Thesmar, 2015, The wacc fallacy: The real effects of using a unique discount rate, *Journal of Finance* forthcoming.
- Kumar, Alok, 2009, Who gambles in the stock market?, *Journal of Finance* 64, 1889–1933.
- , Jeremy Page, and Oliver Spalt, 2011, Religious beliefs, gambling attitudes, and financial market outcomes, *Journal of Financial Economics* 102, 671–708.
- Kuppuswamy, Venkat, and Belen Villalonga, 2010, Does diversification create value in the presence of external financing constraints? Evidence from the 2007-2009 financial crisis, Working Paper, Harvard University.
- Lamont, Owen, 1997, Cash flow and investment: Evidence from internal capital markets, *Journal of Finance* 52, 83–109.
- Lamont, Owen A., and Christopher Polk, 2002, Does diversification destroy value? evidence from the industry shocks, *Journal of Financial Economics* 63, 51 – 77.
- List, John A., 2003, Does market experience eliminate market anomalies?, *Quarterly Journal of Economics* 118, 41–71.
- Maksimovic, Vojislav, and Gordon Phillips, 2002, Do conglomerate firms allocate resources inefficiently across industries? Theory and evidence, *The Journal of Finance* 57, 721–767.
- Malmendier, Ulrike, and Geoffrey Tate, 2005, Ceo overconfidence and corporate investment, *The Journal of Finance* 60, pp. 2661–2700.
- Markowitz, Harry, 1952, The utility of wealth, *Journal of Political Economy* 60, 151–158.
- Martin, Robert, and Bruce Yandle, 1990, State lotteries as duopoly transfer mechanisms, *Public Choice* 64, 253–264.
- Matsusaka, John G, 2001, Corporate diversification, value maximization, and organizational capabilities, *The Journal of Business* 74, 409–431.
- Mikesell, John L., 1994, State lottery sales and economic activity, *National Tax Journal* 47, 165–171.
- Mitton, Todd, and Keith Vorkink, 2007, Equilibrium under-diversification and the preference for skewness, *Review of Financial Studies* 20, 1255–1288.
- , 2011, Why do firms with diversification discounts have higher expected returns?, *Journal of Financial and Quantitative Analysis* 45, 1367–1390.

- Ozbas, Oguzhan, and David S. Scharfstein, 2010, Evidence on the dark side of internal capital markets, *Review of Financial Studies* 23, 581–599.
- Pastor, Lubos, and Pietro Veronesi, 2003, Stock valuation and learning about profitability, *Journal of Finance* 58, 1749–1789.
- , 2006, Was there a NASDAQ bubble in the late 1990s?, *Journal of Financial Economics* 81, 61–100.
- Rajan, Raghuram, Henri Servaes, and Luigi Zingales, 2000, The cost of diversity: The diversification discount and inefficient investment, *The Journal of Finance* 55, pp. 35–80.
- Scharfstein, David S., and Jeremy C. Stein, 2000, The dark side of internal capital markets: Divisional rent-seeking and inefficient investment, *The Journal of Finance* 55, pp. 2537–2564.
- Shin, Hyun-Han, and Rene M. Stulz, 1998, Are internal capital markets efficient?, *The Quarterly Journal of Economics* 113, pp. 531–552.
- Snowberg, Erik, and Justin Wolfers, 2010, Explaining the favorite-longshot bias: Is it risk-love, or misperceptions?, *Journal of Political Economy* 118, 723–746.
- Spalt, Oliver G., 2013, Probability weighting and employee stock options, *Journal of Financial and Quantitative Analysis* 48, 1085–1118.
- Stein, Jeremy C., 1997, Internal capital markets and the competition for corporate resources, *The Journal of Finance* 52, pp. 111–133.
- , 2003, Agency, information, and corporate investment, *Handbook of Economics and Finance* (edited by George Constantinides, Milton Harris, and Rene Stulz).
- Thompson, William N., 2001, *Gambling in America: An Encyclopedia of History, Issues, and Society* (ABC-CLIO, Inc.).
- Tversky, Amos, and Daniel Kahneman, 1992, Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* 5, 297–323.
- Zhang, Yijie, 2006, Individual skewness and the cross-section of average stock returns, Yale University, Working Paper.

**TABLE I**  
**Descriptive Statistics**

This table displays descriptive statistics for the main variables used in our analysis. Panel A reports segment-level variables, Panel B reports firm-level variables for the subset of conglomerate firms, and Panel C reports firm-level variables for standalone firms, all defined in Section I.

Panel A: Segments

| Variable                      | Mean | Median | S.D. | Min.  | 25 <sup>th</sup><br>Perc. | 75 <sup>th</sup><br>Perc. | Max.  | N      |
|-------------------------------|------|--------|------|-------|---------------------------|---------------------------|-------|--------|
| Investment <sub>SEG</sub> (%) | 7.70 | 4.69   | 9.91 | 0.00  | 2.04                      | 9.21                      | 62.58 | 26,867 |
| CashFlow <sub>SEG</sub>       | 0.15 | 0.15   | 0.20 | -0.73 | 0.07                      | 0.23                      | 0.91  | 26,867 |
| Size <sub>SEG</sub> (\$bn)    | 0.95 | 0.15   | 2.24 | 0.00  | 0.03                      | 0.69                      | 14.58 | 26,867 |
| Skew <sub>SEG</sub>           | 0.01 | 0.00   | 0.03 | -0.07 | -0.01                     | 0.03                      | 0.12  | 26,867 |
| Volatility <sub>SEG</sub>     | 0.50 | 0.48   | 0.16 | 0.18  | 0.39                      | 0.60                      | 1.02  | 26,867 |
| Return <sub>SEG</sub>         | 0.13 | 0.13   | 0.23 | -0.50 | -0.01                     | 0.27                      | 0.78  | 26,867 |
| Q <sub>SEG</sub>              | 1.39 | 1.31   | 0.35 | 0.97  | 1.13                      | 1.54                      | 3.09  | 26,867 |
| Q <sub>CORE</sub>             | 1.37 | 1.30   | 0.34 | 0.97  | 1.12                      | 1.52                      | 2.96  | 26,867 |
| Small <sub>SEG</sub>          | 0.47 | 0.00   | 0.50 | 0.00  | 0.00                      | 1.00                      | 1.00  | 26,867 |

Panel B: Conglomerate Firms

| Variable                       | Mean  | Median | S.D.  | Min.  | 25 <sup>th</sup><br>Perc. | 75 <sup>th</sup><br>Perc. | Max.  | N      |
|--------------------------------|-------|--------|-------|-------|---------------------------|---------------------------|-------|--------|
| Investment <sub>FIRM</sub> (%) | 6.47  | 4.76   | 6.40  | 0.00  | 2.65                      | 8.06                      | 49.33 | 10,919 |
| CashFlow <sub>FIRM</sub>       | 0.07  | 0.08   | 0.10  | -0.73 | 0.04                      | 0.11                      | 0.35  | 11,596 |
| Size <sub>FIRM</sub> (\$bn)    | 2.23  | 0.44   | 4.71  | 0.00  | 0.08                      | 1.86                      | 26.44 | 11,596 |
| Q <sub>FIRM</sub>              | 1.38  | 1.21   | 0.62  | 0.56  | 1.01                      | 1.56                      | 5.43  | 11,593 |
| Age <sub>FIRM</sub>            | 25.70 | 25.00  | 14.87 | 2.00  | 12.00                     | 39.00                     | 55.00 | 11,596 |
| Focus <sub>FIRM</sub>          | 0.68  | 0.72   | 0.23  | 0.04  | 0.52                      | 0.87                      | 1.00  | 11,596 |

Panel C: Standalone Firms

| Variable                       | Mean  | Median | S.D.  | Min.  | 25 <sup>th</sup><br>Perc. | 75 <sup>th</sup><br>Perc. | Max.  | N      |
|--------------------------------|-------|--------|-------|-------|---------------------------|---------------------------|-------|--------|
| Investment <sub>FIRM</sub> (%) | 6.71  | 3.69   | 9.00  | 0.00  | 1.30                      | 8.16                      | 49.33 | 65,319 |
| CashFlow <sub>FIRM</sub>       | 0.01  | 0.06   | 0.20  | -0.73 | -0.01                     | 0.12                      | 0.35  | 76,142 |
| Size <sub>FIRM</sub> (\$bn)    | 0.76  | 0.08   | 2.71  | 0.00  | 0.02                      | 0.34                      | 26.44 | 76,142 |
| Q <sub>FIRM</sub>              | 1.70  | 1.34   | 1.00  | 0.56  | 1.03                      | 2.04                      | 5.43  | 76,142 |
| Age <sub>FIRM</sub>            | 13.74 | 10.00  | 11.28 | 2.00  | 6.00                      | 18.00                     | 55.00 | 76,142 |

**TABLE II**  
**Conglomerate Investment and Segment Skewness**

This table presents results for OLS regressions with segment investment as dependent variable. In models (1) to (4) the dependent variable segment investment is defined as segment-level capital expenditures in period  $t$  scaled by segment-level assets in period  $t - 1$ . In models (5) to (7) the dependent variable is defined as segment investment less the mean asset weighted investment across all standalone companies in the same FF48-industry. Segment-level skewness ( $\text{Skew}_{\text{SEG}}$ ) measures the expected skewness in the segment's FF48-industry.  $\text{Small}_{\text{SEG}}$  is one if segments are both, not in the top-tercile of relative size, and not in the top-tercile of segment size across all segments in the sample and fiscal year, and zero otherwise. Specifications (4) and (7) show coefficients of the interaction terms only for variables of interest. All explanatory variables are lagged by one year. The  $t$ -statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

| Dep. Var.:  | Segment Investment |                   |                   |                   | Industry-Adjusted<br>Segment Investment |                   |                   |
|---|--------------------|-------------------|-------------------|-------------------|---|-------------------|-------------------|
| Variable  | (1)                | (2)               | (3)               | (4)               | (5)                                     | (6)               | (7)               |
| $\text{Skew}_{\text{SEG}}$  | 5.402<br>(1.72)    | 4.979<br>(1.69)   | -3.455<br>(-0.97) | -2.382<br>(-0.69) | 8.782<br>(2.63)                         | -0.818<br>(-0.22) | -0.463<br>(-0.13) |
| $\text{Skew}_{\text{SEG}} \times \text{Small}_{\text{SEG}}$       |                    |                   | 15.219<br>(3.43)  | 12.909<br>(2.93)  |   | 17.624<br>(3.81)  | 16.560<br>(3.61)  |
| $\text{Volatility}_{\text{SEG}}$                                  | -0.044<br>(-0.04)  | -0.011<br>(-0.01) | -0.974<br>(-0.83) | -0.170<br>(-0.15) | -4.309<br>(-5.81)                       | -5.442<br>(-6.88) | -4.930<br>(-6.43) |
| $\text{Volatility}_{\text{SEG}} \times \text{Small}_{\text{SEG}}$ |                    |                   | 1.741<br>(1.47)   | 0.400<br>(0.34)   |   | 2.774<br>(2.41)   | 1.896<br>(1.65)   |
| $\text{Return}_{\text{SEG}}$                                      | 1.223<br>(3.14)    | 1.170<br>(3.01)   | 1.450<br>(3.35)   | 1.608<br>(3.69)   | 0.468<br>(1.16)                         | 1.055<br>(2.42)   | 1.168<br>(2.71)   |
| $\text{Return}_{\text{SEG}} \times \text{Small}_{\text{SEG}}$     |                    |                   | -0.637<br>(-1.09) | -0.915<br>(-1.57) |   | -1.234<br>(-2.07) | -1.371<br>(-2.30) |
| $\text{Small}_{\text{SEG}}$                                       | 0.803<br>(3.60)    | 0.736<br>(3.36)   | -0.202<br>(-0.31) | 1.266<br>(0.76)   | 0.694<br>(3.04)                         | -0.699<br>(-1.11) | 0.792<br>(0.47)   |
| $\text{CashFlow}_{\text{SEG}}$                                    | 3.123<br>(4.09)    | 3.244<br>(4.23)   | 3.282<br>(4.28)   | 10.649<br>(10.89) | 3.022<br>(4.06)                         | 3.098<br>(4.16)   | 9.616<br>(9.26)   |
| $\text{CashFlow}_{\text{FIRM}}$                                   | 8.725<br>(5.91)    | 8.346<br>(5.65)   | 8.340<br>(5.64)   | 4.399<br>(2.34)   | 8.286<br>(5.42)                         | 8.258<br>(5.40)   | 5.054<br>(2.46)   |
| $\text{Skew}_{\text{FIRM}}$                                       | -5.703<br>(-1.30)  | -5.564<br>(-1.28) | -3.034<br>(-0.69) | -3.657<br>(-0.84) | -3.496<br>(-0.78)                       | -0.719<br>(-0.16) | -1.307<br>(-0.29) |
| $\text{Q}_{\text{SEG}}$   | 2.960<br>(5.12)    | 2.655<br>(4.52)   | 2.577<br>(4.44)   | 2.731<br>(4.64)   | -0.799<br>(-1.81)                       | -0.899<br>(-2.08) | -0.916<br>(-2.02) |
| $\text{Q}_{\text{CORE}}$  | -0.429<br>(-1.10)  | 0.222<br>(0.49)   | 0.265<br>(0.58)   | -0.452<br>(-0.89) | -0.587<br>(-1.50)                       | -0.500<br>(-1.28) | -1.059<br>(-2.35) |
| $\text{Size}_{\text{FIRM}}$                                       | -0.177<br>(-2.63)  | -0.213<br>(-3.09) | -0.210<br>(-3.05) | -0.230<br>(-3.12) | -0.190<br>(-2.68)                       | -0.187<br>(-2.63) | -0.236<br>(-3.07) |
| $\text{Age}_{\text{FIRM}}$  | -0.652<br>(-3.56)  | -0.681<br>(-3.84) | -0.690<br>(-3.89) | -0.496<br>(-2.64) | -0.484<br>(-2.53)                       | -0.508<br>(-2.64) | -0.259<br>(-1.29) |
| $\text{Focus}_{\text{FIRM}}$                                      | 0.122<br>(0.25)    | -0.214<br>(-0.43) | -0.214<br>(-0.43) | -0.415<br>(-0.82) | 0.296<br>(0.58)                         | 0.271<br>(0.54)   | -0.051<br>(-0.10) |
| Year FE   | Yes                | Yes               | Yes               | Yes               | Yes                                     | Yes               | Yes               |
| Industry FE (Seg)   | Yes                | Yes               | Yes               | Yes               | No                                      | No                | No                |
| Industry FE (Firm)  | No                 | Yes               | Yes               | Yes               | No                                      | No                | No                |
| All Interacted  | No                 | No                | No                | Yes               | No                                      | No                | Yes               |
| Observations  | 26,867             | 26,867            | 26,867            | 26,867            | 26,862                                  | 26,862            | 26,862            |
| Adjusted $R^2$  | 0.110              | 0.117             | 0.118             | 0.123             | 0.021                                   | 0.022             | 0.027             |

**TABLE III****Conglomerate Investment, Segment Skewness, and Unobservables**

This table presents results for OLS regressions with segment investment as dependent variable. The baseline regression models in Table II (column (2) and (3)) are rerun in five different specifications: In model (1) the dependent variable is industry-adjusted segment investment less the asset weighted average industry-adjusted segment investment across all the segments of the conglomerate firm (Rajan, Serveas, and Zingales (2000)). Model (2) includes industry-fiscal year fixed effects, model (3) is estimated in changes, model (4) includes firm fixed effects, and model (5) includes segment fixed effects. Panel A reports results without and Panel B with the segment size interaction. The  $t$ -statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

Panel A: Effect on the Average Segment

|                     | Firm-Industry<br>Adj. | Ind x Year FE    | Changes         | Firm FE         | Segment FE      |
|---------------------|-----------------------|------------------|-----------------|-----------------|-----------------|
| Variable            | (1)                   | (2)              | (3)             | (4)             | (5)             |
| Skew <sub>SEG</sub> | 9.624<br>(2.99)       | 10.681<br>(2.05) | 2.142<br>(0.84) | 2.480<br>(0.78) | 2.975<br>(0.81) |
| Controls            | Yes                   | Yes              | Yes             | Yes             | Yes             |
| Fixed Effect        | Year                  | Ind x Year       | Year            | Firm            | Segment         |
| Observations        | 26,862                | 26,867           | 20,909          | 26,867          | 26,867          |
| Adjusted $R^2$      | 0.005                 | 0.110            | 0.024           | 0.229           | 0.422           |

Panel B: Effect on Small versus Large Segments

|  | Firm-Industry<br>Adj. | Ind x Year FE      | Changes            | Firm FE           | Segment FE        |
|--|-----------------------|--------------------|--------------------|-------------------|-------------------|
| Variable                                   | (1)                   | (2)                | (3)                | (4)               | (5)               |
| Skew <sub>SEG</sub>                        | 2.359<br>(0.68)       | 1.527<br>(0.27)    | -2.275<br>(-0.71)  | -5.155<br>(-1.57) | -3.696<br>(-1.04) |
| Skew <sub>SEG</sub> × Small <sub>SEG</sub> | 13.283<br>(3.37)      | 14.950<br>(3.16)   | 6.383<br>(1.84)    | 18.130<br>(3.94)  | 8.696<br>(1.97)   |
| Small <sub>SEG</sub>                       | -37.513<br>(-3.84)    | -25.033<br>(-0.52) | -39.437<br>(-1.84) | 3.884<br>(0.23)   | -4.251<br>(-0.19) |
| Controls                                   | Yes                   | Yes                | Yes                | Yes               | Yes               |
| Fixed Effect                               | Year                  | Ind x Year         | Year               | Firm              | Segment           |
| Observations                               | 26,862                | 26,867             | 20,909             | 26,867            | 26,867            |
| Adjusted $R^2$                             | 0.006                 | 0.110              | 0.024              | 0.229             | 0.422             |



**TABLE IV**  
**Robustness Checks**

This table presents robustness checks. The baseline regression models (2) and (3) from Table II are rerun in different specifications: (1) uses an alternative skewness measure ( $\text{Skew}_{\text{SEG}}$ ), which is calculated using 5th (95th) percentile instead of the 1st (99th) percentile of the return distribution, (2) computes skewness from net income growth, using as an input net income growth for all standalone firms in Compustat in industry  $i$  and fiscal year  $t$  that have positive net income in  $t$  and  $t - 1$ , (3) computes skewness measure from the distribution of sales growth, using as in input sales growth for all standalone firms in Compustat in industry  $i$  and fiscal year  $t$ , (4) uses the MAX measure proposed in Bali, Cakici, and Whitelaw (2011) as alternative skewness measure; it is defined as the average maximum daily return of all firms in the same FF48-industry over the preceding fiscal year, (5) uses an alternative skewness measure ( $\text{Skew}_{\text{SEG}}$ ), which is MSA specific and excludes in its estimation all firms headquarter in the respective MSA, (6) uses inverse of absolute segment size instead of  $\text{Small}_{\text{SEG}}$ , (7) uses inverse of relative segment size instead of  $\text{Small}_{\text{SEG}}$ . Standard errors allow for clustering at the firm level.

|                                   |                      | Skew <sub>SEG</sub> | <i>t</i> – value | Skew <sub>SEG</sub> ×<br>Small <sub>SEG</sub> | <i>t</i> – value | Obs.   | Adj. <i>R</i> <sup>2</sup> |
|-----------------------------------|----------------------|---------------------|------------------|---|------------------|--------|----------------------------|
| Alternative Skewness Measures     |                      |                     |                  |   |                  |        |                            |
| (1)                               | Skewness 5%          | 3.885               | 0.87             | 14.725  | 2.35             | 26,867 | 0.118                      |
|                                   |                      | 10.757              | 2.58             |   |                  | 26,867 | 0.117                      |
| (2)                               | Skew of NI Growth    | 0.099               | 0.32             | 1.248   | 2.20             | 26,628 | 0.118                      |
|                                   |                      | 0.635               | 2.38             |   |                  | 26,628 | 0.118                      |
| (3)                               | Skew of Sales Growth | -0.353              | -1.39            | 1.424   | 3.26             | 26,808 | 0.118                      |
|                                   |                      | 0.315               | 1.44             |   |                  | 26,808 | 0.117                      |
| (4)                               | MAX measure          | -0.519              | -0.17            | 8.106   | 2.52             | 26,867 | 0.117                      |
|                                   |                      | 4.619               | 1.35             |   |                  | 26,867 | 0.117                      |
| (5)                               | Skewness MSA         | -0.729              | -0.24            | 12.354  | 3.29             | 26,867 | 0.118                      |
|                                   |                      | 5.529               | 2.13             |   |                  | 26,867 | 0.117                      |
| Alternative Segment Size Measures |                      |                     |                  |   |                  |        |                            |
| (6)                               | Absolute Size        | 22.589              | 3.31             | 3.704   | 3.37             | 26,867 | 0.119                      |
|                                   |                      | 5.304               | 1.68             |   |                  | 26,867 | 0.118                      |
| (7)                               | Relative Size        | 0.716               | 0.21             | 0.308   | 3.40             | 26,867 | 0.120                      |
|                                   |                      | 5.303               | 1.67             |   |                  | 26,867 | 0.119                      |

**TABLE V**  
**Conglomerates and Standalone Firms – Matching Results**

This table presents results for OLS regressions with the difference in investment between matched pairs, segment minus standalone firms, as dependent variable. Matching between segments and standalone firms is based on (1) FF48-industry and year, (2) FF48-industry, year and size using the standalone firm closest in size to the segment, (3) FF48-industry, year and size using the standalone firm closest in size to the segment within a matching threshold of  $\pm 20\%$ , (4) FF48-industry, year and size using the standalone firm closest in size to the segment within a matching threshold of  $\pm 20\%$ , and age. Age categories are 1-10 and 10+ years. Repeat matches are not allowed. Segment and standalone firm investment is defined as capital expenditures in period  $t$  scaled by assets in period  $t - 1$ .  $\text{Skew}_{\text{SEG}}$  measures the expected skewness in the FF48-industry.  $\text{Q}_{\text{SEG}}$  is defined as median Tobin's Q of the FF48-industry.  $\Delta\text{CashFlow}$  is the difference between cash flows over assets of the matched pair. All explanatory variables are lagged by one year. The estimation is done for three samples (i) all matched segments, (ii) only small segments in the bottom tercile of the relative size distribution of matched segments, (iii) only large segments in the top tercile of the relative size distribution of matched segments. The  $t$ -statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the industry-year level.

| Match by:  | Dep. Var.: $\Delta$ Investment |                         |                               |                                    |
|--|--------------------------------|-------------------------|-------------------------------|------------------------------------|
|  | Industry, Year                 | Industry, Year,<br>Size | Industry, Year,<br>Size limit | Industry, Year,<br>Size limit, Age |
|  | (1)                            | (2)                     | (3)                           | (4)                                |
| <i>All Segments</i>  |                                |                         |                               |                                    |
| Constant   | 0.141<br>(0.35)                | -0.243<br>(-0.62)       | -0.314<br>(-0.79)             | -1.076<br>(-1.73)                  |
| $\text{Skew}_{\text{SEG}}$                                     | 5.813<br>(2.30)                | 7.696<br>(2.97)         | 8.928<br>(3.27)               | 11.100<br>(2.46)                   |
| $\text{Q}_{\text{SEG}}$  | -0.361<br>(-1.18)              | 0.054<br>(0.20)         | 0.056<br>(0.20)               | 0.818<br>(1.84)                    |
| $\Delta\text{CashFlow}$  | 5.837<br>(14.82)               | 5.266<br>(11.17)        | 6.013<br>(12.30)              | 4.635<br>(7.51)                    |
| Observations   | 24,205                         | 17,271                  | 16,114                        | 8,736                              |
| Adjusted $R^2$   | 0.018                          | 0.014                   | 0.017                         | 0.012                              |
| <i>Conglomerate Segment is in Bottom Relative Size Tercile</i> |                                |                         |                               |                                    |
| $\text{Skew}_{\text{SEG}}$                                     | 15.823<br>(3.49)               | 11.275<br>(2.31)        | 13.570<br>(2.68)              | 17.110<br>(2.34)                   |
| Controls   | Yes                            | Yes                     | Yes                           | Yes                                |
| Observations   | 8,074                          | 5,763                   | 5,377                         | 2,917                              |
| Adjusted $R^2$   | 0.011                          | 0.008                   | 0.011                         | 0.010                              |
| <i>Conglomerate Segment is in Top Relative Size Tercile</i>    |                                |                         |                               |                                    |
| $\text{Skew}_{\text{SEG}}$                                     | 1.509<br>(0.36)                | 4.475<br>(1.05)         | 4.804<br>(1.10)               | 4.928<br>(0.71)                    |
| Controls   | Yes                            | Yes                     | Yes                           | Yes                                |
| Observations   | 8,064                          | 5,748                   | 5,365                         | 2,905                              |
| Adjusted $R^2$   | 0.021                          | 0.022                   | 0.026                         | 0.012                              |

**TABLE VI**  
**Value Implications**

This table presents results for OLS, fixed effects, instrumental variable, and treatment effects regressions. The sample consists of standalone firms and conglomerates. The dependent variable is excess value, which is the log difference between firm value and its imputed value as in Berger and Ofek (1995). Each segment of a conglomerate is valued using the median sales multiplier of standalone firms in the same FF48-industry that includes at least five firms. The imputed value of the conglomerate is the sum of the segment values. Conglomerate is a dummy that is 1 if the firm is a conglomerate and 0 otherwise. Skewed is a dummy variable equal to 1 if, in a given year, the conglomerate has a segment operating in an industry with above median expected skewness, which is outside the conglomerate's major FF12-industry. Following Campa and Kedia (2002), the fraction of conglomerate firms in the industry is used as an instrument for conglomerate status in the instrumental variable regressions and the treatment model. The  $t$ -statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

| Variable                          | Dep. Var.: Excess Value |                    |                   |                    |                    |                    |                    |                    |
|-----------------------------------|-------------------------|--------------------|-------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
|                                   | OLS                     |                    | FE                |                    | IV                 |                    | Selection          |                    |
|                                   | (1)                     | (2)                | (3)               | (4)                | (5)                | (6)                | (7)                | (8)                |
| Conglomerate                      | -0.109<br>(-8.82)       | -0.097<br>(-7.14)  | -0.098<br>(-7.62) | -0.106<br>(-7.39)  | 0.042<br>(0.77)    | 0.141<br>(2.15)    | 0.026<br>(1.02)    | 0.110<br>(3.73)    |
| Skewed                            | -0.042<br>(-3.25)       | -0.045<br>(-3.09)  | -0.023<br>(-2.48) | -0.019<br>(-1.81)  | -0.146<br>(-3.34)  | -0.226<br>(-4.35)  | -0.156<br>(-6.80)  | -0.220<br>(-8.31)  |
| Size <sub>FIRM</sub>              | 0.030<br>(12.39)        | 0.225<br>(21.31)   | 0.053<br>(8.68)   | 0.222<br>(13.40)   | 0.026<br>(9.72)    | 0.226<br>(21.29)   | 0.027<br>(23.29)   | 0.226<br>(31.79)   |
| CAPX/Sales                        | 0.376<br>(27.76)        | 0.225<br>(14.67)   | 0.341<br>(21.04)  | 0.231<br>(12.50)   | 0.382<br>(27.99)   | 0.230<br>(14.92)   | 0.381<br>(42.29)   | 0.229<br>(17.00)   |
| EBIT/Sales                        | -0.052<br>(-13.71)      | -0.058<br>(-11.00) | -0.046<br>(-9.10) | -0.070<br>(-8.73)  | -0.051<br>(-13.67) | -0.058<br>(-10.97) | -0.051<br>(-28.73) | -0.058<br>(-23.77) |
| Volatility <sub>Median</sub>      | -0.120<br>(-3.46)       | -0.208<br>(-5.51)  | -0.336<br>(-8.24) | -0.322<br>(-7.22)  | -0.095<br>(-2.69)  | -0.170<br>(-4.35)  | -0.099<br>(-5.69)  | -0.176<br>(-9.14)  |
| Size <sub>FIRM</sub> (Lag1)       |                         | -0.142<br>(-14.42) |                   | -0.217<br>(-21.49) |                    | -0.141<br>(-14.22) |                    | -0.141<br>(-15.23) |
| Size <sub>FIRM</sub> (Lag2)       |                         | -0.136<br>(-20.29) |                   | -0.121<br>(-16.83) |                    | -0.141<br>(-20.57) |                    | -0.140<br>(-24.26) |
| CAPX/Sales (Lag1)                 |                         | 0.033<br>(2.99)    |                   | 0.043<br>(3.12)    |                    | 0.035<br>(3.13)    |                    | 0.034<br>(2.81)    |
| CAPX/Sales (Lag2)                 |                         | 0.064<br>(6.14)    |                   | 0.038<br>(3.39)    |                    | 0.069<br>(6.55)    |                    | 0.068<br>(7.30)    |
| EBIT/Sales (Lag1)                 |                         | -0.003<br>(-2.03)  |                   | -0.001<br>(-0.30)  |                    | -0.003<br>(-2.08)  |                    | -0.003<br>(-2.37)  |
| EBIT/Sales (Lag2)                 |                         | -0.003<br>(-2.67)  |                   | -0.004<br>(-3.06)  |                    | -0.003<br>(-2.52)  |                    | -0.003<br>(-3.01)  |
| Leverage                          |                         | 0.062<br>(3.08)    |                   | 0.085<br>(3.73)    |                    | 0.055<br>(2.68)    |                    | 0.056<br>(5.07)    |
| Size <sub>FIRM</sub> <sup>2</sup> |                         | 0.008<br>(10.48)   |                   | 0.012<br>(8.35)    |                    | 0.008<br>(9.88)    |                    | 0.008<br>(21.94)   |
| Lambda                            |                         |                    |                   |                    |                    |                    | -0.078<br>(-5.54)  | -0.118<br>(-7.33)  |
| Year FE                           | Yes                     | Yes                | Yes               | Yes                | Yes                | Yes                | Yes                | Yes                |
| Firm FE                           | No                      | No                 | Yes               | Yes                | No                 | No                 | No                 | No                 |
| Observations                      | 84,575                  | 65,961             | 84,575            | 65,961             | 84,575             | 65,961             | 84,575             | 65,961             |

**TABLE VII**  
**Geographical Variation in Gambling Propensity and Investment**

This table presents subsample results for OLS regressions with segment-level investment as dependent variable. Panel A reports results without and Panel B with segment size interaction. We split the sample annually into segments of conglomerates located in counties with above or below median ratio of Catholics to Protestants, our measure of local gambling propensity following Kumar, Page, and Spalt (2011). Control variables in Panel A (Panel B) are those used in Table II column (2) (column (3)). County characteristics are total population, fraction of married households, the male-to-female ratio, the fraction of the population aged over 25 with a college degree, the average age of the population, the fraction of minority households, the fraction of the local population living in an urban area, a large MSA dummy, which is one for counties in metropolitan statistical areas (MSA) that are among the 10 largest by population in the year 2000. All explanatory variables are lagged by one year. The  $t$ -statistics for the coefficient estimates are reported in parentheses below the estimates. The table also reports the  $p$ -values from a Wald-test of equality of coefficients for  $\text{Skew}_{\text{SEG}}$  and  $\text{Skew}_{\text{SEG}} \times \text{Small}_{\text{SEG}}$  across regressions (1) and (4), (2) and (5), and (3) and (6), respectively. Standard errors allow for clustering at the firm level.

Panel A: Effect on Average Segment

| Variable  | Dep. Var.: Segment investment |                 |                 |                          |                 |                 |
|---|-------------------------------|-----------------|-----------------|--------------------------|-----------------|-----------------|
|   | Low Gambling Propensity       |                 |                 | High Gambling Propensity |                 |                 |
|   | (1)                           | (2)             | (3)             | (4)                      | (5)             | (6)             |
| $\text{Skew}_{\text{SEG}}$  | 0.810<br>(0.17)               | 0.585<br>(0.12) | 0.803<br>(0.17) | 9.235<br>(2.18)          | 8.735<br>(2.07) | 7.972<br>(1.96) |
| Controls  | Yes                           | Yes             | Yes             | Yes                      | Yes             | Yes             |
| Year & Industry FE (Firm & Seg)   | Yes                           | Yes             | Yes             | Yes                      | Yes             | Yes             |
| County characteristics  | No                            | Yes             | Yes             | No                       | Yes             | Yes             |
| State FE  | No                            | No              | Yes             | No                       | No              | Yes             |
| Observations  | 13,259                        | 13,259          | 13,259          | 12,917                   | 12,917          | 12,917          |
| Adjusted $R^2$  | 0.124                         | 0.125           | 0.131           | 0.096                    | 0.100           | 0.110           |
| Test $\beta_{\text{LOW}} = \beta_{\text{HIGH}}[\text{Skew}_{\text{SEG}}]$ (p-value) |                               |                 |                 | 0.183                    | 0.203           | 0.240           |

Panel B: Effect on Small versus Large Segments

| Variable   | Dep. Var.: Segment investment |                   |                   |                          |                    |                    |
|--|-------------------------------|-------------------|-------------------|--------------------------|--------------------|--------------------|
|  | Low Gambling Propensity       |                   |                   | High Gambling Propensity |                    |                    |
|  | (1)                           | (2)               | (3)               | (4)                      | (5)                | (6)                |
| $\text{Skew}_{\text{SEG}}$   | -1.486<br>(-0.27)             | -1.777<br>(-0.33) | -2.204<br>(-0.41) | -4.673<br>(-0.99)        | -5.051<br>(-1.08)  | -5.613<br>(-1.20)  |
| $\text{Skew}_{\text{SEG}} \times \text{Small}_{\text{SEG}}$  | 5.708<br>(0.86)               | 5.935<br>(0.89)   | 6.325<br>(0.95)   | 23.273<br>(3.74)         | 23.406<br>(3.81)   | 23.421<br>(3.84)   |
| $\text{Small}_{\text{SEG}}$  | 23.243<br>(0.80)              | 21.522<br>(0.74)  | 17.779<br>(0.60)  | -58.024<br>(-2.41)       | -55.296<br>(-2.30) | -49.958<br>(-2.11) |
| Controls   | Yes                           | Yes               | Yes               | Yes                      | Yes                | Yes                |
| Year & Industry FE (Firm & Seg)  | Yes                           | Yes               | Yes               | Yes                      | Yes                | Yes                |
| County characteristics   | No                            | Yes               | Yes               | No                       | Yes                | Yes                |
| State FE   | No                            | No                | Yes               | No                       | No                 | Yes                |
| Observations   | 13,259                        | 13,259            | 13,259            | 12,917                   | 12,917             | 12,917             |
| Adjusted $R^2$   | 0.134                         | 0.134             | 0.139             | 0.108                    | 0.111              | 0.120              |
| Test $\beta_{\text{LOW}} = \beta_{\text{HIGH}}[\text{Skew}_{\text{SEG}}]$ (p-value)                                  |                               |                   |                   | 0.655                    | 0.647              | 0.639              |
| Test $\beta_{\text{LOW}} = \beta_{\text{HIGH}}[\text{Skew}_{\text{SEG}} \times \text{Small}_{\text{SEG}}]$ (p-value) |                               |                   |                   | 0.048                    | 0.046              | 0.049              |

**TABLE VIII**  
**Sample Splits**

The regressions in Table II (column (2) and (3)) are rerun for different subsamples: (i) high (low) changes in annual per capita lottery sales in the conglomerate's state of location (upper and lower tercile), (ii) old (young) conglomerate firm CEO (upper and lower tercile in a given year), in this test we control for CEO tenure, (iii) above (below) median corporate governance quality of the conglomerate measured by the GIM-index, (iv) above (below) median CEO stock ownership in a given year, (v) above (below) median CEO tenure in a given year, we control for age in this test. The  $t$ -statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

Panel A: Change in annual per capita lottery sales in the state of location

|      | Skew <sub>SEG</sub> | $t$ - value | Skew <sub>SEG</sub> $\times$<br>Small <sub>SEG</sub> | $t$ - value | Obs.  | Adj. $R^2$ |
|------|---------------------|-------------|--|-------------|-------|------------|
| High | 9.687               | 1.41        |  |             | 6,692 | 0.109      |
| Low  | 0.797               | 0.13        |  |             | 6,485 | 0.152      |
| High | -1.799              | -0.25       | 22.005   | 2.37        | 6,692 | 0.109      |
| Low  | -1.375              | -0.17       | 3.774  | 0.42        | 6,485 | 0.152      |

Panel B: CEO age

|            | Skew <sub>SEG</sub> | $t$ - value | Skew <sub>SEG</sub> $\times$<br>Small <sub>SEG</sub> | $t$ - value | Obs.  | Adj. $R^2$ |
|------------|---------------------|-------------|--|-------------|-------|------------|
| Young CEOs | 7.804               | 0.96        |  |             | 2,786 | 0.184      |
| Old CEOs   | -4.055              | -0.52       |  |             | 2,503 | 0.204      |
| Young CEOs | -3.955              | -0.39       | 26.654   | 2.01        | 2,786 | 0.185      |
| Old CEOs   | -2.086              | -0.26       | -6.156   | -0.43       | 2,503 | 0.204      |

Panel C: GIM-index

|               | Skew <sub>SEG</sub> | $t$ - value | Skew <sub>SEG</sub> $\times$<br>Small <sub>SEG</sub> | $t$ - value | Obs.  | Adj. $R^2$ |
|---------------|---------------------|-------------|--|-------------|-------|------------|
| Dictatorships | 4.571               | 0.73        |  |             | 4,345 | 0.239      |
| Democracies   | -1.991              | -0.35       |  |             | 6,274 | 0.175      |
| Dictatorships | 0.755               | 0.13        | 13.643   | 1.72        | 4,345 | 0.239      |
| Democracies   | -5.009              | -0.78       | 6.452  | 0.67        | 6,274 | 0.175      |

Panel D: CEO ownership

|                    | Skew <sub>SEG</sub> | $t$ - value | Skew <sub>SEG</sub> $\times$<br>Small <sub>SEG</sub> | $t$ - value | Obs.  | Adj. $R^2$ |
|--------------------|---------------------|-------------|--|-------------|-------|------------|
| High CEO Ownership | 5.180               | 0.74        |  |             | 5,033 | 0.185      |
| Low CEO Ownership  | -5.222              | -0.89       |  |             | 4,928 | 0.174      |
| High CEO Ownership | -3.649              | -0.43       | 18.673   | 1.98        | 5,033 | 0.187      |
| Low CEO Ownership  | -6.256              | -1.15       | 4.410  | 0.34        | 4,928 | 0.174      |

Panel E: CEO tenure

|                  | Skew <sub>SEG</sub> | $t$ - value | Skew <sub>SEG</sub> $\times$<br>Small <sub>SEG</sub> | $t$ - value | Obs.  | Adj. $R^2$ |
|------------------|---------------------|-------------|--|-------------|-------|------------|
| Long CEO Tenure  | 5.161               | 0.95        |  |             | 3,763 | 0.191      |
| Short CEO Tenure | 0.823               | 0.10        |  |             | 3,866 | 0.188      |
| Long CEO Tenure  | -11.925             | -1.16       | 28.747   | 2.15        | 3,763 | 0.193      |
| Short CEO Tenure | -3.781              | -0.65       | 3.600  | 0.32        | 3,866 | 0.188      |

**TABLE IX**  
**Skewness and Investment Opportunities**

This table presents results for OLS regressions with segment investment (Panel A) and investment of standalone firms as dependent variable (Panel B). In Panel A, (1)  $R\&D_{SEG}$  is segment R&D expenses scaled by lagged segment assets, where missing R&D expenses are set to zero, (2)  $SalesGrowth_{SEG}$  is segment sales over lagged sales minus one, (3)  $EmplGrowth_{SEG}$  is total employment growth in the segment's FF48-industry over the preceding year based on Compustat, (4)  $Productivity_{SEG}$  is growth in total sales over total employment in the segments FF48-industry over the preceding year. Control variables from Table II (specifications (2) and (3), respectively) are included but not shown. Standard errors allow for clustering at the firm level.

Panel A: Additional Investment Opportunity Controls

|  | Dep. Var.: Segment Investment |                   |                  |                   |                 |                   |                  |                    |
|--|-------------------------------|-------------------|------------------|-------------------|-----------------|-------------------|------------------|--------------------|
|  | (1)                           | (2)               | (3)              | (4)               | (5)             | (6)               | (7)              | (8)                |
| Skew <sub>SEG</sub>                        | 5.284<br>(1.75)               | -3.523<br>(-0.97) | 5.123<br>(1.74)  | -3.784<br>(-1.05) | 5.187<br>(1.69) | -3.256<br>(-0.91) | 4.9725<br>(1.65) | -3.4527<br>(-0.97) |
| Skew <sub>SEG</sub> × Small <sub>SEG</sub> |                               | 16.186<br>(3.63)  |                  | 16.363<br>(3.67)  |                 | 15.242<br>3.44    |                  | 15.2046<br>(3.43)  |
| SalesGrowth <sub>SEG</sub>                 | 0.460<br>(3.92)               | 0.460<br>(3.93)   |                  |                   |                 |                   |                  |                    |
| R&D <sub>SEG</sub>                         |                               |                   | 13.923<br>(2.03) | 13.886<br>(2.03)  |                 |                   |                  |                    |
| EmplGrowth <sub>SEG</sub>                  |                               |                   |                  |                   | 1.205<br>(1.87) | 1.223<br>(1.89)   |                  |                    |
| Sales/EmplGrowth <sub>SEG</sub>            |                               |                   |                  |                   |                 |                   | 0.3548<br>(0.68) | 0.3412<br>(0.65)   |
| Other Controls                             | Yes                           | Yes               | Yes              | Yes               | Yes             | Yes               | Yes              | Yes                |
| Observations                               | 24,411                        | 24,411            | 24,411           | 24,411            | 26,867          | 26,867            | 26,867           | 26,867             |
| Adjusted $R^2$                             | 0.129                         | 0.129             | 0.128            | 0.128             | 0.117           | 0.118             | 0.117            | 0.118              |

Panel B: Only Standalone Firms

|                           | Dep. Var.: Investment |                    |                   |
|---------------------------|-----------------------|--------------------|-------------------|
|                           | (1)                   | (2)                | (3)               |
| Skew <sub>IND</sub>       | 3.744<br>(1.42)       | -1.119<br>(-0.50)  | -1.191<br>(-0.50) |
| Volatility <sub>IND</sub> | -1.299<br>(-1.89)     | -0.945<br>(-1.16)  | -0.482<br>(-0.57) |
| Return <sub>IND</sub>     | 1.074<br>(3.65)       | 0.823<br>(3.26)    | 0.292<br>(1.03)   |
| CashFlow <sub>FIRM</sub>  | 6.566<br>(13.21)      | 4.996<br>(12.22)   | 2.520<br>(6.87)   |
| Q <sub>IND</sub>          | -1.292<br>(-5.89)     | 0.923<br>(3.23)    | 0.833<br>(2.74)   |
| Q <sub>FIRM</sub>         | 1.366<br>(14.87)      | 1.464<br>(19.53)   | 1.663<br>(21.22)  |
| Size <sub>FIRM</sub>      | 0.199<br>(3.52)       | 0.198<br>(4.38)    | -0.589<br>(-5.42) |
| Age <sub>FIRM</sub>       | -1.264<br>(-9.69)     | -1.305<br>(-12.18) | -0.986<br>(-4.84) |
| Year FE                   | Yes                   | Yes                | Yes               |
| Industry FE               | No                    | Yes                | No                |
| Firm FE                   | No                    | No                 | Yes               |
| Observations              | 30,175                | 30,175             | 30,175            |
| Adjusted $R^2$            | 0.095                 | 0.304              | 0.623             |

**TABLE X**  
**The Skewness-Investment Relation and Uncertainty**

This table presents results for OLS regressions with segment investment as dependent variable.  $\text{RightSkew}_{\text{SEG}}$  ( $\text{LeftSkew}_{\text{SEG}}$ ) is defined as the absolute difference between the 99th and 50th (50th and 1st) percentile of the daily return distribution of stocks in the segment's FF48-industry over the preceding fiscal year. The control variables are the same as in Table II (column (2) and (3)). All explanatory variables are lagged by one year. The  $t$ -statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

|  | Dep. Var.: Segment Investment |                    |                    |                    |
|--|-------------------------------|--------------------|--------------------|--------------------|
|  | (1)                           | (2)                | (3)                | (4)                |
| $\text{RightSkew}_{\text{SEG}}$                                  | 7.354<br>(0.78)               | 7.020<br>(0.75)    | -12.778<br>(-1.14) | -14.279<br>(-1.26) |
| $\text{RightSkew}_{\text{SEG}} \times \text{Small}_{\text{SEG}}$ |                               |                    | 33.475<br>(2.16)   | 35.321<br>(2.31)   |
| $\text{LeftSkew}_{\text{SEG}}$                                   | -10.902<br>(-1.25)            | -10.056<br>(-1.17) | 11.174<br>(1.03)   | 13.240<br>(1.21)   |
| $\text{LeftSkew}_{\text{SEG}} \times \text{Small}_{\text{SEG}}$  |                               |                    | -36.925<br>(-2.66) | -38.911<br>(-2.83) |
| Controls   | Yes                           | Yes                | Yes                | Yes                |
| Year FE  | Yes                           | Yes                | Yes                | Yes                |
| Industry FE (Seg)  | Yes                           | Yes                | Yes                | Yes                |
| Industry FE (Firm)   | No                            | Yes                | No                 | Yes                |
| Observations   | 26,867                        | 26,867             | 26,867             | 26,867             |
| Adjusted $R^2$   | 0.110                         | 0.117              | 0.110              | 0.117              |

# Conglomerate Investment, Skewness, and the CEO Long Shot Bias

## Internet Appendix

This appendix presents additional results to accompany the paper "Conglomerate Investment, Skewness, and the CEO Long Shot Bias". The contents are as follows:

**Appendix A** presents variable definitions for all variables used in the paper.

**Appendix B** presents robustness checks for the valuation results in Table VI in the paper.

**Appendix C** presents additional robustness checks for the baseline regression specification in Table II, referred to in Section II.C.

**Appendix D** discusses the potential impact of investor biases.

**Appendix E** presents a theoretical model with mean-variance-skewness preferences of the CEO.



## Appendix A: Description of the Data

TABLE AI

### Variable Definitions and Sources

This table defines the main variables used in the empirical analysis. The data sources are: (i) ARDA: Association of Religion Data Archives, (ii) Compustat, (iii) CRSP: Center for Research on Security Prices, (iv) ExecuComp, (v) Andrew Metrick's website.

| Variable name                  | Description  | Source    |
|--------------------------------|--|-----------|
| <b>Segment-level variables</b> |  |           |
| $Investment_{SEG}$             | Segment-level capital expenditures [CAPX] scaled by segment-level assets [AT] at the previous fiscal year end.   | Compustat |
| $Skew_{SEG}$                   | Expected skewness is estimated for each segment $i$ in fiscal year $t$ as: $SKEW_{i,t} = \frac{(P_{99}-P_{50})-(P_{50}-P_1)}{(P_{99}-P_1)}$ , where $P_j$ is the $j$ th percentile of the pooled return distribution of daily returns of all firms with share codes 10 and 11 in CRSP in the same FF48-industry over the 12 months prior to and including the last month of the conglomerate's fiscal year $t$ . | CRSP      |
| $Return_{SEG}$                 | Value-weighted monthly rebalanced return in the segment's FF48-industry, based on all firms with share codes 10 and 11 in CRSP in the same FF48-industry over the 12 months prior to and including the last month of the conglomerate's fiscal year $t$ .  | CRSP      |
| $Volatility_{SEG}$             | Annualized median idiosyncratic volatility in the segment's FF48-industry, calculated from the residual of a Fama and French (1993) three-factor model estimated on daily data over the 12 months prior to and including the last month of the conglomerate's fiscal year $t$ .  | CRSP      |
| $Size_{SEG}$                   | Natural logarithm of segment-level sales [SALE].   | Compustat |
| $Small_{SEG}$                  | =1 if segments are both, not in the top-tercile of relative size, and not in the top-tercile of segment size across all segments in the sample and fiscal year, otherwise zero.  | Compustat |
| $CashFlow_{SEG}$               | Segment-level cash flows [OPS+DP] scaled by segment-level assets [AT].   | Compustat |
| $\Delta CashFlow$              | Difference between $CashFlow_{SEG}$ and $CashFlow_{FIRM}$ of the matched standalone firm.  | Compustat |
| $\Delta Investment$            | Difference between $Investment_{SEG}$ and $Investment_{FIRM}$ of the matched standalone firm.  | Compustat |
| $Q_{SEG}$                      | Median bounded Tobin's Q of all standalone firms that operate in the same FF48-industry as the segment. The bounded Tobin's Q is defined following Ozbas and Scharfstein (2010) as $MVA/(0.9 \times BVA + 0.1 \times MVA)$ , for further details see $Q_{FIRM}$ .  | Compustat |

(continued...)

**TABLE AI (Continued)**  
**Variable Definitions and Sources**

| Variable name               | Description  | Source               |
|-----------------------------|--|----------------------|
| <b>Firm-level variables</b> |  |                      |
| $Investment_{FIRM}$         | Firm's total capital expenditures [CAPX] scaled by firm's total assets [AT] at the previous fiscal year end.   | Compustat            |
| $CashFlow_{FIRM}$           | Firm's total cash flows [IB+DP] scaled by firm's total assets [AT].  | Compustat            |
| $Size_{FIRM}$               | Natural logarithm of firm's sales [SALE].  | Compustat            |
| $Skew_{FIRM}$               | Asset weighted average of $Skew_{SEG}$ across all segments of the firm.  | CRSP                 |
| $Age_{FIRM}$                | Natural logarithm of the current year plus one minus the year in which the firm first appeared in the Compustat North America database.  | Compustat            |
| $Focus_{FIRM}$              | Ratio of the core (largest) segment sales and the firm's total sales [SALE]. Equals one for standalone firms by definition.  | Compustat            |
| $Q_{FIRM}$                  | The bounded Tobin's Q is defined following Ozbas and Scharfstein (2010) as $MVA / (0.9 \times BVA + 0.1 \times MVA)$ , where BVA is the book value of assets [AT] and MVA is the market value of common equity [CSHO*PRCC_F] plus the book value of assets [AT] minus the book value of common equity [CEQ] and balance sheet deferred taxes [TXDITC]. | Compustat            |
| $Q_{IND}$                   | Defined as $Q_{SEG}$ .   | Compustat            |
| Leverage                    | Long-term debt [DLTT] over total assets [AT].  | Compustat            |
| CAPX/Sales                  | Capital expenditures [CAPX] scaled by sales [SALE].  | Compustat            |
| EBIT/Sales                  | Earnings before interest and taxes [EBITDA - DP] scaled by sales [SALE].   | Compustat            |
| <b>Other variables used</b> |  |                      |
| CPRATIO                     | Ratio of Catholic population to Protestant population in the county where the conglomerate firm's headquarter is located.  | ARDA, US Census      |
| CEO Age                     | Age of the conglomerate firm's CEO at the fiscal year end.   | ExecuComp            |
| CEO Ownership               | Percentage stock ownership of the conglomerate firm's CEO.   | ExecuComp            |
| CEO Tenure                  | Number of years the CEO has been at the helm of the conglomerate firm.   | ExecuComp            |
| GIM-Index                   | Following Gompers, Ishii, and Metrick (2003), minimum 1 (low entrenchment), maximum 19 (high entrenchment).  | A. Metrick's website |
| $\Delta LotteryTicketSales$ | Annual change in per capita lottery expenditures in the state where the conglomerate firm's headquarter is located.  | NASPL                |

## Appendix B: Value Implications – Extended Specifications

**TABLE BI**

### Value Implications – Extended Specifications

This table tests for the robustness of the valuation results in Table VI and the presence of an investor channel. Panel A repeats the analysis from Table V using *#Skewed* instead of *Skewed*. *#Skewed* is the number of segments in the conglomerate operating in industries with above median expected skewness, which are outside the conglomerate’s major FF12-industry. Panel B repeats the analysis from Table VI using the Hoberg-Phillips (HP100) instead of the FF48-industry classification for conglomerate segments and standalones. Panel C repeats the analysis from Table VI using the asset-weighted average skewness of all segments where  $Small_{SEG} = 1$ , instead of the dummy variable *Skewed*. Panel D repeats the analysis from Table VI with the additional control variable  $Diversity_{RSZ}$  defined following Rajan, Serveas, and Zingales (2000) as the standard deviation of asset-weighted segment Tobin’s Q ( $Q_{SEG}$ ) for the firm divided by the equally weighted average  $Q_{SEG}$  in the firm. Panel E repeats the analysis from Table VI with the additional control variable  $Diversity_{LP}$  defined following Lamont and Polk (2002) as the within-firm standard deviation of the median investment to capital ratio in the segment’s FF48-industry. The median investment to capital ratio is estimated among standalone firms. Base controls and additional controls are those from Table VI. The  $t$ -statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

Panel A: Number of Skewed Segments

| Variable                                    | Dep. Var.: Excess Value |                   |                   |                   |                   |                   |                   |                   |
|---|-------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|   | OLS                     |                   | FE                |                   | IV                |                   | Selection         |                   |
|   | (1)                     | (2)               | (3)               | (4)               | (5)               | (6)               | (7)               | (8)               |
| Conglomerate                                | -0.110<br>(-9.02)       | -0.097<br>(-7.28) | -0.096<br>(-7.48) | -0.103<br>(-7.19) | 0.033<br>(0.64)   | 0.126<br>(2.06)   | -0.044<br>(-2.40) | 0.008<br>(0.37)   |
| <i>#Skewed</i>                              | -0.035<br>(-3.45)       | -0.040<br>(-3.48) | -0.028<br>(-3.67) | -0.026<br>(-3.12) | -0.102<br>(-3.45) | -0.159<br>(-4.55) | -0.076<br>(-5.82) | -0.106<br>(-7.03) |
| Base controls                               | Yes                     | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               |
| Additional controls                         | No                      | Yes               | No                | Yes               | No                | Yes               | No                | Yes               |
| Year FE                                     | Yes                     | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               |
| Firm FE                                     | No                      | No                | Yes               | Yes               | No                | No                | No                | No                |
| Observations                                | 84,575                  | 65,961            | 84,575            | 65,961            | 84,575            | 65,961            | 84,575            | 65,961            |
| Angrist-Pischke F-Test for weak instruments |                         |                   |                   |                   | <0.001            | <0.001            |                   |                   |

Panel B: Using Hoberg-Phillips Industry Classification

| Variable                                    | Dep. Var.: Excess Value |                   |                   |                   |                   |                   |                   |                   |
|---|-------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|   | OLS                     |                   | FE                |                   | IV                |                   | Selection         |                   |
|   | (1)                     | (2)               | (3)               | (4)               | (5)               | (6)               | (7)               | (8)               |
| Conglomerate                                | -0.107<br>(-8.12)       | -0.097<br>(-6.58) | -0.089<br>(-6.34) | -0.096<br>(-6.07) | -0.027<br>(-0.37) | 0.048<br>(0.55)   | -0.049<br>(-1.56) | -0.014<br>(-0.39) |
| <i>Skewed</i>                               | -0.026<br>(-2.04)       | -0.028<br>(-1.97) | -0.027<br>(-2.86) | -0.027<br>(-2.56) | -0.075<br>(-1.23) | -0.142<br>(-1.97) | -0.077<br>(-2.72) | -0.101<br>(-3.12) |
| Base controls                               | Yes                     | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               |
| Additional controls                         | No                      | Yes               | No                | Yes               | No                | Yes               | No                | Yes               |
| Year FE                                     | Yes                     | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               |
| Firm FE                                     | No                      | No                | Yes               | Yes               | No                | No                | No                | No                |
| Observations                                | 84,386                  | 65,761            | 84,386            | 65,761            | 84,386            | 65,761            | 84,386            | 65,761            |
| Angrist-Pischke F-Test for weak instruments |                         |                   |                   |                   | <0.001            | <0.001            |                   |                   |

**TABLE BI (Continued)**  
**Value Implications – Extended Specifications**

Panel C: Value-weighted Skewed Segments

| Variable                                    | Dep. Var.: Excess Value |                   |                    |                    |                   |                   |                   |                   |
|---|-------------------------|-------------------|--------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|   | OLS                     |                   | FE                 |                    | IV                |                   | Selection         |                   |
|   | (1)                     | (2)               | (3)                | (4)                | (5)               | (6)               | (7)               | (8)               |
| Conglomerate                                | -0.114<br>(-9.62)       | -0.095<br>(-7.28) | -0.094<br>(-12.53) | -0.097<br>(-11.48) | -0.005<br>(-0.11) | 0.085<br>(1.50)   | 0.002<br>(0.08)   | 0.097<br>(3.78)   |
| Weighted average skew                       | -1.542<br>(-2.53)       | -1.283<br>(-2.86) | -0.960<br>(-2.15)  | -0.845<br>(-1.93)  | -3.198<br>(-3.13) | -4.593<br>(-3.08) | -3.851<br>(-5.73) | -5.976<br>(-7.08) |
| Base controls                               | Yes                     | Yes               | Yes                | Yes                | Yes               | Yes               | Yes               | Yes               |
| Additional controls                         | No                      | Yes               | No                 | Yes                | No                | Yes               | No                | Yes               |
| Year FE                                     | Yes                     | Yes               | Yes                | Yes                | Yes               | Yes               | Yes               | Yes               |
| Firm FE                                     | No                      | No                | Yes                | Yes                | No                | No                | No                | No                |
| Observations                                | 81,480                  | 63,608            | 81,480             | 63,608             | 81,480            | 63,608            | 81,480            | 63,608            |
| Angrist-Pischke F-Test for weak instruments |                         |                   |                    |                    | <0.001            | <0.001            |                   |                   |

Panel D: Controlling for Diversity (Rajan, Servaes, and Zingales)

| Variable                                    | Dep. Var.: Excess Value |                   |                   |                   |                   |                   |                   |                   |
|---|-------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|   | OLS                     |                   | FE                |                   | IV                |                   | Selection         |                   |
|   | (1)                     | (2)               | (3)               | (4)               | (5)               | (6)               | (7)               | (8)               |
| Conglomerate                                | -0.049<br>(-0.77)       | -0.002<br>(-0.03) | -0.113<br>(-3.32) | -0.095<br>(-2.56) | 1.824<br>(2.26)   | 3.180<br>(3.34)   | 0.074<br>(1.71)   | 0.186<br>(3.79)   |
| Skewed                                      | -0.042<br>(-3.22)       | -0.045<br>(-3.07) | -0.023<br>(-2.84) | -0.018<br>(-2.08) | -0.088<br>(-3.78) | -0.133<br>(-4.33) | -0.154<br>(-6.71) | -0.217<br>(-8.18) |
| Diversity <sub>RSZ</sub>                    | -0.072<br>(-0.99)       | -0.114<br>(-1.40) | 0.017<br>(0.43)   | -0.013<br>(-0.31) | -2.208<br>(-2.36) | -3.784<br>(-3.43) | -0.059<br>(-1.37) | -0.095<br>(-1.95) |
| Base controls                               | Yes                     | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               |
| Additional controls                         | No                      | Yes               | No                | Yes               | No                | Yes               | No                | Yes               |
| Year FE                                     | Yes                     | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               |
| Firm FE                                     | No                      | No                | Yes               | Yes               | No                | No                | No                | No                |
| Observations                                | 84,575                  | 65,961            | 84,575            | 65,961            | 84,575            | 65,961            | 84,575            | 65,961            |
| Angrist-Pischke F-Test for weak instruments |                         |                   |                   |                   | <0.001            | <0.001            |                   |                   |

Panel E: Controlling for Diversity (Lamont and Polk)

| Variable                                    | Dep. Var.: Excess Value |                   |                    |                    |                   |                   |                   |                   |
|---|-------------------------|-------------------|--------------------|--------------------|-------------------|-------------------|-------------------|-------------------|
|   | OLS                     |                   | FE                 |                    | IV                |                   | Selection         |                   |
|   | (1)                     | (2)               | (3)                | (4)                | (5)               | (6)               | (7)               | (8)               |
| Conglomerate                                | -0.097<br>(-7.01)       | -0.069<br>(-4.27) | -0.096<br>(-11.70) | -0.107<br>(-11.06) | 0.071<br>(1.10)   | 0.213<br>(2.62)   | 0.033<br>(1.29)   | 0.125<br>(4.22)   |
| Skewed                                      | -0.040<br>(-3.11)       | -0.042<br>(-2.91) | -0.023<br>(-2.82)  | -0.018<br>(-2.06)  | -0.135<br>(-3.28) | -0.191<br>(-4.20) | -0.150<br>(-6.54) | -0.208<br>(-7.82) |
| Diversity <sub>LP</sub>                     | -0.571<br>(-2.21)       | -1.338<br>(-3.51) | -0.110<br>(-0.76)  | -0.017<br>(-0.08)  | -1.628<br>(-2.80) | -5.011<br>(-4.45) | -0.542<br>(-3.27) | -1.251<br>(-5.60) |
| Base controls                               | Yes                     | Yes               | Yes                | Yes                | Yes               | Yes               | Yes               | Yes               |
| Additional controls                         | No                      | Yes               | No                 | Yes                | No                | Yes               | No                | Yes               |
| Year FE                                     | Yes                     | Yes               | Yes                | Yes                | Yes               | Yes               | Yes               | Yes               |
| Firm FE                                     | No                      | No                | Yes                | Yes                | No                | No                | No                | No                |
| Observations                                | 84,565                  | 65,951            | 84,565             | 65,951             | 84,565            | 65,951            | 84,565            | 65,951            |
| Angrist-Pischke F-Test for weak instruments |                         |                   |                    |                    | <0.001            | <0.001            |                   |                   |

## Appendix C: Additional Robustness Checks

**TABLE CI**  
**Additional Robustness Checks**

This table presents robustness checks. The baseline regression models (2) and (3) from Table II are rerun in different specifications: (1) uses Hoberg-Phillips 100 industry classification instead of FF48, (2) includes the coskewness between the segment's FF48-industry and the market following Harvey and Siddique (2000), (3) excludes all segment operating in a new economy industry (SIC code 3570 to 3579, 3661, 3674, 5045, 5961, or 7370 to 7379), (4) excludes small segments with less than \$10 million in sales, (5) includes the vega of the CEO's option package estimated following Chava and Purnanandam (2010), (6) includes an overconfident CEO dummy, which equals one if the CEO holds vested options that are at least 67% in the money at the last fiscal year end; average moneyness of the CEOs option portfolio is estimated following Hirshleifer, Low, and Teoh (2012), (7) includes segment asset betas estimated using FF48-industry portfolio returns as in Kruger, Landier, and Thesmar (2015). Standard errors allow for clustering at the firm level.

|     |                               | Skew <sub>SEG</sub> | $t$ – value | Skew <sub>SEG</sub> ×<br>Small <sub>SEG</sub> | $t$ – value | Obs.   | Adj. $R^2$ |
|-----|-------------------------------|---------------------|-------------|---|-------------|--------|------------|
| (1) | Using HP Industries           | -2.174              | -0.72       | 6.209   | 2.02        | 24,920 | 0.122      |
|     |                               | 2.743               | 1.12        |   |             | 24,920 | 0.121      |
| (2) | Control for Coskewness        | -3.465              | -0.97       | 15.131  | 3.41        | 26,867 | 0.118      |
|     |                               | 5.339               | 1.70        |   |             | 26,867 | 0.117      |
| (3) | Exclude New Economy           | -4.569              | -1.22       | 17.045  | 3.62        | 22,810 | 0.123      |
|     |                               | 5.502               | 1.64        |   |             | 22,810 | 0.123      |
| (4) | Segment Assets > \$10 million | -5.100              | -1.47       | 17.188  | 3.72        | 23,090 | 0.153      |
|     |                               | 4.375               | 1.40        |   |             | 23,090 | 0.153      |
| (5) | Control for Vega              | 0.025               | 0.01        | 14.428  | 1.84        | 9,209  | 0.167      |
|     |                               | 5.498               | 1.06        |   |             | 9,209  | 0.166      |
| (6) | Control for Overconfidence    | 1.037               | 0.20        | 13.167  | 1.73        | 8,613  | 0.168      |
|     |                               | 4.034               | 0.74        |   |             | 8,613  | 0.167      |
| (7) | Control for KLT Beta          | -3.417              | -0.96       | 15.337  | 3.46        | 26,867 | 0.118      |
|     |                               | 5.082               | 1.68        |   |             | 26,867 | 0.117      |

## Appendix D: Long Shot Bias of Investors

The recent asset pricing literature finds that some investors like positive skewness in stock returns (e.g., Kumar (2009), Boyer, Mitton, and Vorkink (2010)). It is therefore sensible to ask if a better interpretation for the skewness-investment relation is that investors, and not CEOs, have a long shot bias. (Of course, investor biases and CEO biases are not mutually exclusive.)

One piece of evidence comes from the valuation discount regressions in Table VI. Those regressions can be interpreted as a simple test of the relative strength of CEO versus investor long shot bias. Under the null hypothesis that market participants have a long shot bias, all else equal, we should observe that conglomerates with skewed segments trade at a *premium* because conglomerates invest more in these segments, which is what investors find attractive. Conversely, if the skewness-investment relation reflects a CEO bias, we should observe a discount. The data favor the latter alternative. Effectively, the data is consistent with the view that the many analysts and the thousands of investors who follow typical large public companies have at least some ability to collectively judge when a company is not allocating capital efficiently.

This provides some *prima facie* evidence against an investor bias interpretation, but the evidence could still be consistent with more elaborate theories of investor biases. For example, the above argument does not take into account that combining skewed segments into a conglomerate might erode overall skewness. Investors who like skewness may therefore prefer to invest in standalones, which could generate a skewness discount for those conglomerates with greater skewness-reduction relative to standalones (e.g., Mitton and Vorkink (2011)). While this channel may contribute to explaining the discount, it does not by itself explain why conglomerates tilt budgets towards skewed segments, and why conglomerates invest more into skewed segments than standalones, which are the central findings in our paper. Perhaps, CEOs in conglomerates have an incentive to cater to long shot biased shareholders by overinvesting in high skewness segments to partially counter the skewness erosion. However, this raises the question why CEOs who care about shareholder preferences would form conglomerates that erode skewness in the first place. Moreover, the fact that CEOs in firms with worse corporate governance (“dictatorship” firms) investment more in high skewness segments (Table VIII) does not fit well with the idea that investment in skewed segments is reflecting shareholders preferences.

To investigate this in more detail, we compute a direct measure of skewness erosion (“excess skewness”) proposed by Mitton and Vorkink (2011) as well as the lagged price quintile of the stock (PRANK) which Mitton and Vorkink (2011) show is important in their setup. Table D.I. shows that, although the additional data requirements eliminate half of our original sample, adding these variables to our valuation regressions in Table VI does not alter our results substantially. This shows that the valuation discount for conglomerates with a skewed segment is not due to the skewness erosion effect.

In sum, while the existence of a long shot bias for some investors itself is plausible, the data on the skewness-investment relation is more accurately and more parsimoniously described by the CEO long shot bias.

**TABLE DI**  
**Value Implications – Controlling for Excess Skewness**

This table tests for the robustness of the valuation results in Table VI and shows results from adding a control for skewness erosion (excess skewness) to the valuation discount regressions in Table VI. Excess skewness is the difference between the return skewness of a firm and its imputed skewness. Return skewness is the third standardized moment of past 12 monthly returns. Imputed skewness is the weighted average of the skewness measures from each segment. For each segment in a given FF48-industry, skewness is the median return skewness of all standalone firms in the FF48-industry. PRANK is the lagged price quintile among CRSP stocks, measured at the end of the calendar year. Base controls and additional controls are those from Table VI. The *t*-statistics for the coefficient estimates are reported in parentheses below the estimates. Standard errors allow for clustering at the firm level.

| Variable                                    | Dep. Var.: Excess Value |                   |                   |                   |                   |                   |                   |                   |
|---|-------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|   | OLS                     |                   | FE                |                   | IV                |                   | Selection         |                   |
|   | (1)                     | (2)               | (3)               | (4)               | (5)               | (6)               | (7)               | (8)               |
| Conglomerate                                | -0.123<br>(-8.73)       | -0.123<br>(-8.22) | -0.118<br>(-7.53) | -0.129<br>(-7.42) | -0.008<br>(-0.13) | 0.108<br>(1.54)   | -0.010<br>(-0.34) | 0.081<br>(2.36)   |
| Skewed                                      | -0.052<br>(-3.43)       | -0.046<br>(-2.81) | -0.024<br>(-2.05) | -0.012<br>(-0.95) | -0.127<br>(-2.69) | -0.211<br>(-3.85) | -0.146<br>(-5.45) | -0.216<br>(-7.07) |
| Ex. Skew. And PRANK                         | Yes                     | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               |
| Base controls                               | Yes                     | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               |
| Additional controls                         | No                      | Yes               | No                | Yes               | No                | Yes               | No                | Yes               |
| Year FE                                     | Yes                     | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               | Yes               |
| Firm FE                                     | No                      | No                | Yes               | Yes               | No                | No                | No                | No                |
| Observations                                | 45,209                  | 37,868            | 45,209            | 37,868            | 45,209            | 37,868            | 45,209            | 37,868            |
| Angrist-Pischke F-Test for weak instruments |                         |                   |                   |                   | <0.001            | <0.001            |                   |                   |

## Appendix E: A Specific Model using Mean-Variance-Skewness Preferences

In this appendix we present one specific model to motivate the CEO long shot bias. There are potentially many others. We model the capital allocation decision as a simple portfolio choice problem with the CEO as a biased decision maker. Our point of departure is the standard mean-variance portfolio choice framework, and we capture the CEO long shot bias by extending the framework to incorporate skewness.<sup>1</sup>

Consider a conglomerate consisting of  $N$  segments. Each segment  $i$  is endowed with  $\omega_i$  units of capital available for investment.  $\omega$  can be thought of as the investment budget segments could raise on their own from either existing projects or external financing. We normalize the overall conglomerate-wide size of the investment budget to  $\sum_{i=1}^N \omega_i = 1$ . The CEO's task, made possible by virtue of her control rights, is to optimally reallocate the investment budget across segments. She therefore chooses an optimal vector  $X = [x_1, \dots, x_N]'$ , where the elements of  $X$  are non-negative and denote the final capital budget allocated to segments 1 to  $N$ . Since the overall size of the budget is one,  $x_i$  can also be thought of as the fraction of the available investment budget allocated to segment  $i$ . Returns from investing  $R = [r_1, \dots, r_N]'$  are exogenously determined by the production technology and, for simplicity, independent of the amount invested. The overall return from this allocation is then  $R_{FIRM} = X'R$ , and the CEO chooses  $X$  to maximize:

$$\begin{aligned} \pi(X) &= E(R_{FIRM}) - \tau \text{var}(R_{FIRM}) + \phi \text{skew}(R_{FIRM}) \\ &= X'\mu - \tau X'\Sigma X + \phi X'M(X \otimes X) \end{aligned} \tag{E1}$$

Here, the parameters  $\tau > 0$ , and  $\phi > 0$  govern how much the CEO cares about variance and expected skewness of returns, respectively,  $\mu$  is the vector of expected returns,  $\Sigma$  is the covariance matrix with standard elements, and  $M$  is an appropriately sized matrix (as in de Athayde and Flôres Jr (2004)) of expected skewness with elements  $M_{ijk} = E[(r_i - \mu_i)(r_j - \mu_j)(r_k - \mu_k)]$ , where indexes  $i$ ,  $j$ , and  $k$  denote segments, and  $\otimes$  is the Kronecker product. To keep the model tractable, we specify  $M$  such that we vary only the expected skewness of segment 1, which means we set all terms  $M_{ijk}$  to zero except  $i = j = k = 1$ . The firm's representative investor has mean-variance preferences with the same parameter  $\tau$  as the CEO. Hence, we can think of  $E(R_{FIRM}) - \tau \text{var}(R_{FIRM})$  as the risk-adjusted return on the investment, which shareholders would like to see maximized. This assumption allows for an easy interpretation of the model, but is completely inconsequential for the predictions we derive below unless otherwise indicated.

**Interpretation of the model.** We want to use the model to provide a simple benchmark for thinking about the impact of “gut feeling”. We therefore assume that the CEO *thinks* she is maximizing the risk-adjusted return  $E(R_{FIRM}) - \tau \text{var}(R_{FIRM})$ , while she is actually maximizing

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<sup>1</sup>Similar versions of this mean-variance-skewness model are well-known in the portfolio choice literature (e.g., Harvey, Liechty, Liechty, and Müller (2010), de Athayde and Flôres Jr (2004)) and the behavioral asset pricing literature (e.g., Mitton and Vorkink (2007)).



$\pi(X)$ . Valuation subjectivity and gut feel lead her to systematically favor long-shots, and we capture this feature in the last term:  $\phi \text{skew}(R_{FIRM})$ . Hence, the ultimate decision is driven by a conscious part, which is concerned with shareholder value maximization, and an unconscious part which induces the long shot bias. There are no additional frictions: the CEO tries, but systematically fails, to maximize shareholder value.<sup>2</sup>

There are two ways of looking at the model, which are both consistent with the motivation for the long shot bias. First, we can view it as a model of preferences and focus on the parameter  $\phi$  for a given skewness structure  $M > 0$ .  $\phi$  then measures how much the CEO likes skewness and could be loosely interpreted as an index of over-weighting the right tail of the return distribution as in a prospect theory model with probability weighting (e.g., Barberis and Huang (2008), Spalt (2013)). Second, the model can capture biases in beliefs if we treat the elements of  $M$  for a given  $\phi > 0$  as parameters of interest. For example, a high value for  $M_{111}$  can capture the effect of being optimistic about the upside potential of a currently “hot”, and therefore very salient industry, such as technology around the year 2000. Both interpretations are plausible, and it is a feature of the model that it can capture both. It is not our aim to distinguish between preferences and beliefs.

Five predictions follow from this structure (proofs below):

PREDICTION E1: *The more skewness in the expected returns of segment 1, i.e., the larger  $M_{111}$ , the higher the capital allocation to segment 1.*

PREDICTION E2: *The stronger the preference for skewness ( $\phi$ ) for a given value of  $M_{111} > 0$ , the higher the capital allocation to segment 1.*

PREDICTION E3: *The CEO destroys shareholder value by distorting the capital budget if  $M_{111} > 0$ .*

PREDICTION E4: *The impact of skewness on investment is larger in conglomerates than in standalone firms.*

**The impact of segment size.** In empirical work, the standard variable of interest is investment scaled by a measure of segment size, i.e.  $x/S$ , where  $S$  denotes segment size. The model above implies that  $x/S$  changes more with skewness if  $S$  is smaller. The reason is simple but powerful: a one dollar change in the investment budget leads to a larger change in investment relative to segment size for smaller segments. We derive the following prediction below:

PREDICTION E5: *The impact of skewness on investment over assets is stronger for smaller segments.*

Figure E1 summarizes the main predictions of the model for the two-segment case.

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<sup>2</sup>Note that most of our empirical predictions do not depend on whether we assume the CEO consciously knows she is taking  $\phi \text{skew}(R_{FIRM})$  into account; we can therefore understand most results also by appealing to heterogeneous skewness preferences between CEO and shareholders. We emphasize the subconscious aspect of the long shot preference, however, because it maps more directly to what CEOs describe as “gut feeling”, and because some of our findings, in particular regarding CEO pay, argue against a model in which CEOs are consciously trading off shareholder value for skewness.

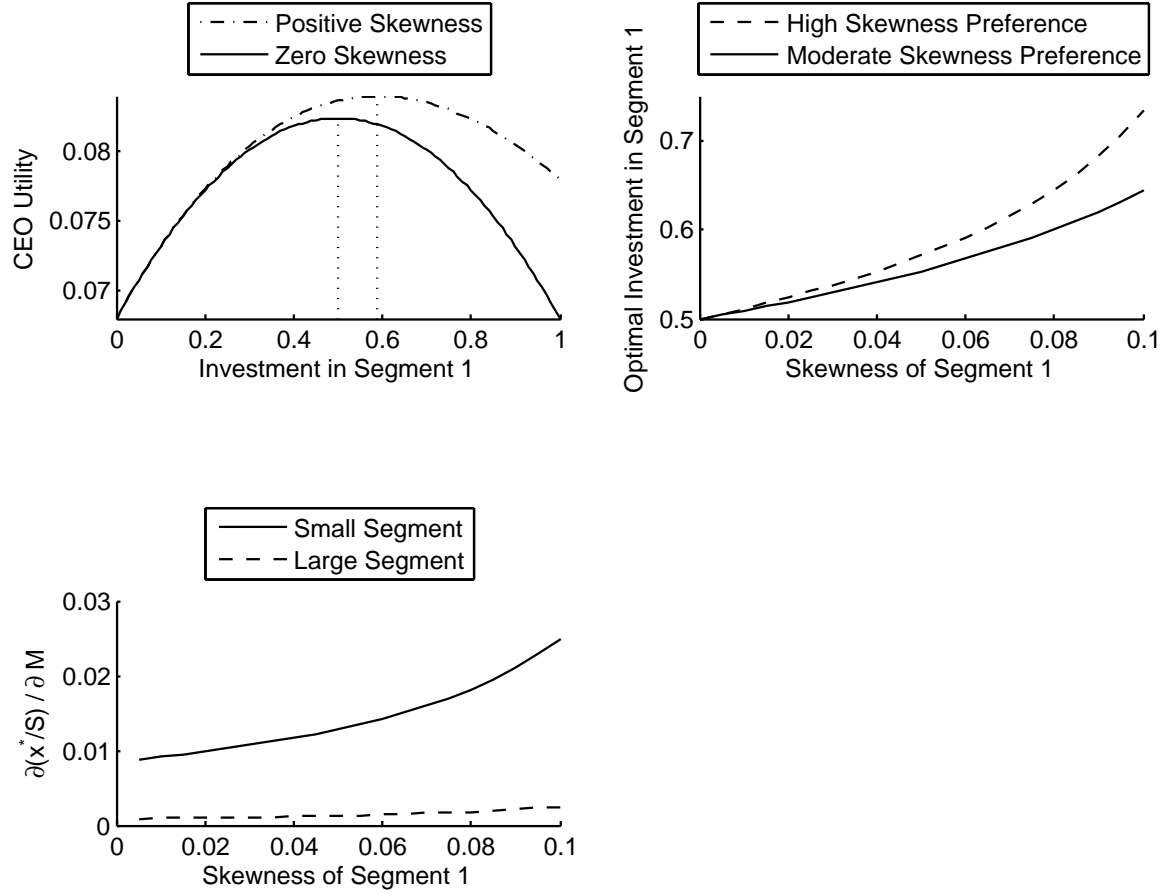


Figure E1: **Impact of Skewness on Capital Allocation in the Two-Segment Case.** Parameter values  $\mu_1 = 0.1$ ,  $\mu_2 = 0.1$ ,  $\sigma_1 = 0.4$ ,  $\sigma_2 = 0.4$ ,  $\rho = 0.1$ ,  $\phi = 0.1333$  (baseline skewness preference value),  $\phi = 0.1667$  (high skewness preference value),  $\tau = 0.2$ .

**Proofs of Predictions E1 to E3.** Our argument is as follows: we will show first that Predictions E1 to E3 hold for the case with two segments,  $n = 2$ . Then, we will show that this already proves the more general case with  $n \geq 2$  segments.

For a two asset portfolio, requiring invested capital to sum to one, and  $0 < x < 1$ , equation (E1) becomes:

$$\begin{aligned}\pi(X) &= E(R_{FIRM}) - \tau \text{var}(R_{FIRM}) + \phi \text{skew}(R_{FIRM}) \\ &= x\mu_1 + (1-x)\mu_2 - \tau(x^2\sigma_1^2 + 2x(1-x)\sigma_{12} + (1-x)^2\sigma_2^2) + \phi x^3 M_{111}.\end{aligned}\tag{E2}$$

The associated first-order condition is:

$$E'(R_{FIRM}) - \tau \text{var}'(R_{FIRM}) + \phi \text{skew}'(R_{FIRM}) = 0,\tag{E3}$$

where  $E'$ ,  $\text{var}'$  and  $\text{skew}'$  denote partial derivatives with respect to investment  $x$ . We assume the first-order condition is necessary and sufficient for a maximum, i.e.  $\pi''(X) < 0$ , and denote the associated optimal value of  $x$  by  $x^*$ .

We can then derive the main predictions using the implicit function theorem:

$$\text{sgn}\left(\frac{\partial x^*}{\partial M_{111}}\right) = \text{sgn}\left(\frac{\partial \phi \text{skew}'(R_{FIRM})}{\partial M_{111}}\right) = \text{sgn}\left(\phi 3(x^*)^2\right).\tag{E4}$$

Since by assumption  $\phi > 0$ , it follows that  $\phi 3(x^*)^2 > 0$  and therefore  $\frac{\partial x^*}{\partial M_{111}} > 0$ . This proves prediction E1.

Using the implicit function theorem on  $\phi$  for a given  $M_{111} > 0$ , yields:

$$\text{sgn}\left(\frac{\partial x^*}{\partial \phi}\right) = \text{sgn}\left(\frac{\partial \phi \text{skew}'(R_{FIRM})}{\partial \phi}\right) = \text{sgn}\left(3(x^*)^2 M_{111}\right).\tag{E5}$$

The last term in brackets is positive for any given  $M_{111} > 0$ . This proves prediction E2.

Since the problem is strictly convex there is a unique investment level  $x^*$  that maximizes  $\pi(X)$ . Unless we are in the knife-edge case where investors have the same preferences as CEOs, utility of the representative investor is strictly lower under the portfolio allocation chosen by the CEO than it would be if the investor could pick the optimal portfolio herself. Assuming mean-variance preferences for the representative investor, but  $\phi > 0$  for CEOs, as we do in the text is sufficient (but not necessary). This proves prediction E3.

Since we have been completely general about the mean, variance, and covariances of asset 2, the above predictions hold for *any* portfolio of assets. Hence, the above case for  $n = 2$  proves the general case  $n \geq 2$  as well since we can redefine asset 2 to be the portfolio of assets  $n = 2, \dots, N$ .

**Prediction E4.** Segments could only invest  $\omega$  when operated on their own. Since  $\omega$  does not depend on skewness, the prediction follows immediately.

**Prediction E5.** We show directly that  $\frac{\partial(x^*/S)}{\partial M_{111}}$  decreases in segment size  $S > 0$ :

$$\text{sgn}\left(\frac{\partial(x^*/S)}{\partial M_{111}\partial S}\right) = \text{sgn}\left(\frac{\partial(1/S)}{\partial S}\frac{\partial x^*}{\partial M_{111}}\right) = \text{sgn}\left(-\frac{1}{S^2}\phi 3(x^*)^2\right), \quad (\text{E6})$$

where the first equality follows from noting that  $x^*$  does not depend on  $S$ , and the second equality follows from using the results from equation (E4). The last term in brackets is negative for  $\phi > 0$ . This proves prediction E5.